4

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This paper reports several experiments that investigated how performance feedback in a computer-based training environment affected students' acquisition of cognitive skills requiring substantial practice. College students worked on category-search or electronic troubleshooting tasks; problems were presented, responses were recorded, and performance feedback was given using microcomputers. We studied the impact of receiving information about (a) temporal trends in one's own performance (i.e., intrapersonal feedback alone) and (b) temporal trends in both one's own and others' performance (i.e., joint intrapersonal and interpersonal feedback). In regard to intrapersonal feedback alone, we assessed how different types of "absolute" performance information (e.g., weighted vs. unweighted averages of reaction times on previous trials) affected students' learning. Results indicated that these manipulations had only weak effects. In regard to joint intrapersonal and interpersonal (over)

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19. Abstract (continued)

feedback, we assessed how different types of "relative" performance information (e.g., superiority vs. inferiority vis-a-vis others) affected students' learning. Here, evidence revealed that the type of feedback students received influenced how well they performed. It was suggested that the impact of intrapersonal and interpersonal feedback will be affected by the amount of practice time needed to achieve proficiency. Feedback may have a larger effect with extended training periods representative of normal classroom instruction.

Abstract

This paper reports several experiments that investigated how performance feedback in a computer-based training environment affected students' acquisition of cognitive skills requiring substantial practice. College students worked on category-search or electronic troubleshooting tasks; problems were presented, responses were recorded, and performance feedback was given using microcomputers. We studied the impact of receiving information about (a) temporal trends in one's own performance (i.e., intrapersonal feedback alone) and (b) temporal trends in both one's own and others' performance (i.e., joint intrapersonal and interpersonal feedback). In regard to intrapersonal feedback alone, we assessed how different types of "absolute" performance information (e.g., weighted vs. unweighted averages of reaction times on previous trials) affected students' learning. Results indicated that these manipulations had only weak effects. In regard to joint intrapersonal and interpersonal feedback, we assessed how different types of "relative" performance information (e.g., superiority vs.inferiority vis-a-vis others) affected students' learning. Here, evidence revealed that the type of feedback students received influenced how well they performed. It was suggested that the impact of intrapersonal and interpersonal feedback will be affected by the amount of practice time needed to achieve proficiency. Feedback may have a larger effect with extended training periods representative of normal classroom instruction.

FEEDBACK EFFECTS IN COMPUTER-BASED SKILL TRAINING

Motivation in Computer-Based Instruction

Our work is based on the assumption that skill acquisition in computer environments, as in conventional classrooms, is determined by several factors (cf. Carroll, 1963; Slavin, 1986). One factor, student aptitude, is not under teacher control, at least in the short run. Other factors, including the quality of the instruction, the appropriateness of the instruction to the student's skills, and the amount of time the student is given to learn the material, are quite amenable to teacher control. Finally, the last factor, the student's motivation to work on instructional tasks, is jointly affected by both the student and the teacher.

It is important to recognize that each of these factors is necessary, but not sufficient, for effective instruction. In attempting to conceptualize the relationships among these factors, it is useful to adopt a multiplicative model. Such a model has two implications. First, it implies that instruction will be maximally effective when student aptitude, instructional quality, instructional appropriateness, time on task, and student motivation are all high. Second, it implies that instruction will be ineffective if even one of these factors is low. It should be noted that, in many circumstances, these factors are not orthogonal. For example, it would not be surprising if low instructional quality reduced student motivation, or if instructional appropriateness was easier to achieve with medium-aptitude than with high- or low-aptitude students.

Most researchers interested in computer-based instruction are at least implicitly aware of the importance of the five factors just mentioned. Moreover, if questioned, they would probably acknowledge that these factors can, at least to some extent, compensate for and influence one another. In spite of this awareness, however, there is a striking imbalance in the amount of explicit attention that has been devoted to the various determinants of learning in computer environments. Instructional quality issues, such as clarity of lesson objectives, organization of information, and use of examples and summaries, have received extensive attention. In contrast, motivational issues have been largely neglected.

Many definitions of motivation in general and achievement motivation in particular have been proposed over the years. For our purposes, the definitions offered by Dweck and Elliott (1983) are appropriate. These authors define motivation as "contemporaneous, dynamic psychological factors that influence such phenomena as the choice, initiation, direction, magnitude, persistence, resumption, and quality of goal-directed (including cognitive) activity (p. 645)." Dweck and Elliott identify two types of achievement goals (those involving learning and those involving performance) and define achievement motivation as "psychological factors (other than ability) that affect the adoption and pursuit of these goals (p. 646)."

One perspective on motivation and learning suggests that the key to effortful performance is intrinsic interest in the task. According to this position, which is well-articulated by Lepper and his colleagues (e.g., Lepper, 1985; Lepper & Chabay, 1985; Lepper & Malone, 1985; Malone & Lepper, 1985), motivational problems can be averted

by using tasks (such as games) that are "fun" to work on. Although such tasks may well prove useful in enhancing motivation for some learners in some subjects, it seems premature to conclude that intrinsically interesting tasks will provide a general solution to the problem of motivational deficits. Some educational theorists, such as Slavin (1986), declare that it is impossible to make all subjects intrinsically interesting to all students, and hence extrinsic incentives are essential to produce adequate levels of effort. Other theorists, such as Lepper (1985) and Deci and Ryan (1985), point out that substantial theoretical disagreement exists regarding the psychological underpinnings of intrinsic interest (e.g., some theories emphasize the importance of challenge, others stress curiosity, and still others highlight control). This controversy suggests that the construction of intrinsically interesting tasks in a variety of subject domains will not be easy. Finally, it is not clear that intrinsically interesting tasks, even if they could be created, would necessarily be the most effective way to teach many important skills. As Lepper (1985) has suggested, the impact of intrinsic motivation on learning is not well understood, and there may be circumstances under which features of intrinsically interesting tasks actually inhibit learning.

A second perspective on motivation and learning emphasizes the use of external reinforcers as a means of enhancing performance. Many programs have been developed in which students are rewarded for good performance and/or punished for poor performance. These techniques can be quite effective if students perceive clear contingencies between performance and reinforcement and if reinforcers have high value. Given these constraints, it is clear that successful reinforcement programs are easier to implement in some environments (e.g., military training installations) than in others (e.g., inner-city high schools).

Acquisition of Component Skills in Complex Tasks

Our research seeks to clarify the impact of motivation on learning when intrinsic interest is low. We are concerned with the acquisition of the component skills necessary for efficient performance on complex tasks, such as electronic troubleshooting. Moreover, we are concerned with skills that can be taught to individuals and small groups using computer-based instruction in controlled settings. A number of important task domains satisfy these criteria. For example, in reading and arithmetic, as in electronic troubleshooting, many component skills must become automated. If the training environment fails to produce active, sustained practice by the student, then this automation will not occur, and the component skills will be neither acquired nor incorporated into higher level skills.

Component skills must be practiced for long periods of time in order for the learner to shift from controlled processing, which is slow, serial, and effortful, to automatic processing, which is fast, parallel, and fairly effortless (Schneider, Dumais, & Shiffrin, 1984; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). For example, in learning integration formulas in calculus, students need to practice the basic formulas many times in order to execute reliably a complex series of substitutions without error. Work in W. Schneider's lab on a variety of tasks indicates that some students quit during the initial acquisition phases because the resource demands are so high that the task seems impossible. Moreover, many students fail to exert effort on the task after modest skill levels are achieved. It is very

difficult for even good students to practice a component task for thousands of trials. Typically, after the first 200 trials, students' performance is accurate and moderately fast. The improvements per hundred additional trials may be too small to seem worth the effort. The absence of salient performance improvement makes it difficult for students to maintain the motivation necessary for sustained practice. Such practice is essential, however, when students shift to a higher task level. When such a shift occurs, lack of practice of component skills can have devastating effects.

Varieties of Performance Feedback

Most techniques for increasing student motivation assume that certain types of performance feedback facilitate task-related effort, whereas other types inhibit such effort. If so, then research designed to identify the characteristics of effective feedback may prove quite useful in improving instructional design.

In situations where learning requires a long period of practice, the student typically receives feedback about his or her performance at more than one point in time (see Exhibit 1). This information can be received either continuously (i.e., after every trial) or intermittently. In the intermittent case, feedback episodes can be separated by either a constant or a variable number of trials. Regardless of the frequency with which information is received, it can either reflect performance on the last trial alone or aggregated performance across some set of previous trials. When aggregated performance is involved, the number of trials in the set can vary, as can the weighting function that is used to combine information from different trials (e.g., each trial might be weighted equally, or some trials might be weighted more heavily than others).

In addition to these parameters, performance feedback can vary on other dimensions as well. For example, feedback can reveal either absolute performance (e.g., reaction time in milliseconds) or relative performance (e.g., "graded" reaction time vis-a-vis some standard). It is important to note that, compared to absolute performance, relative performance is both more "evaluative" and less "precise." Moreover, the receipt of feedback can be either obligatory (in that students receive performance information whether or not they desire it) or voluntary (in that students can choose to receive or avoid performance information). In either case, students might or might not be given control over the specific form of feedback that they receive (e.g., continuous vs. intermittent, absolute vs. relative, private vs. public). Finally, of course, the temporal pattern of feedback can vary. The number of possible temporal patterns is immense. Potentially important aspects of such patterns include: the slope and intercept of the performance curve; the shape of the curve (linear; nonlinear); and the degree of variability around the curve (both average variability around the entire curve and specific variability around particular portions of the curve). Exhibit 2 illustrates several temporal patterns that might occur in students' performance (Ryan & Levine, 1981).

Our discussion so far has focused on the student's receipt of information regarding temporal trends in his or her own performance, which can be labeled intrapersonal feedback. It is also possible, of course, for the student to receive information about temporal

trends in both (a) his or her own performance and (b) another person's performance (or the performances of several other persons). In this case, the student gets _interpersonal_ as well as intrapersonal feedback.

In order to facilitate discussion of joint interpersonal and intrapersonal feedback, we will make three simplifying assumptions. First, we will assume that the student receives feedback about another's performance each time that he or she receives feedback about his or her own performance. If the two types of feedback are not always available, or if the student has the option to avoid one or both types, then a substantially more complicated situation can arise. We have found, for example, that a subject whose performance is increasing over time is equally interested in seeing the performance of someone who is improving at a faster rate and someone who is improving at a slower rate. In contrast, a subject whose performance is decreasing over time is much more interested in seeing the performance of someone who is deteriorating at a faster rate than someone who is deteriorating at a slower rate (Levine & Green, 1984). The second simplifying assumption that we will make is that the student receives feedback about his or her own and another's performance at only two points in time (Time 1 and Time 2). This assumption eliminates the possibility of curvilinear relationships between performance and time. Finally, we will consider only ordinal differences between performances. This means that, rather than dealing with the magnitude of the difference between Performance X and Performance Y, we will only be concerned with whether X is larger, smaller, or equal to Y.

Even in the extremely simplified situation just described, a large number of relationships are possible (see Exhibit 3). In this table, A1 refers to Person A's performance at Time 1, A2 refers to Person A's performance at Time 2, and so on for Person B. The check marks in the table refer to the possible _intrapersonal_ relationships between A1 and A2 and between B1 and B2, and to the possible _interpersonal_ relationships between A1 and B1 and between A2 and B2. Note that the intrapersonal relationships are _intertemporal_ (that is, they cross the two time periods), whereas the interpersonal relationships are _intratemporal_ (that is, they remain within a single time period). We have left out the relationships between A1 and B2 and between A2 and B1 (which are both interpersonal and intertemporal), although there are certainly cases in which they might be interesting. Clearly, investigators who are interested in studying the joint impact of interpersonal and intrapersonal feedback on motivation must consider a wide range of possible performance patterns.

To illustrate how the relationships in the table might look if they were depicted on graphs, we have drawn a subset of them (see Exhibit 4). This figure shows the nine relationships that could arise in the lower right cell of Exhibit 3 (where A1 < A2 and A1 < B1).

Performance Feedback and Motivation: A Brief Overview of Relevant Research

Having made the case that performance feedback on tasks involving extended practice is potentially quite complex, we now turn to the question of what prior research has revealed about the motivational consequences of such feedback. This question is both difficult and easy to answer. It is difficult, because a substantial amount of research has been conducted

on related issues, and this work has not always yielded consistent findings. It is easy, because little effort has been explicitly devoted to investigating how performance feedback affects motivation on extended practice tasks. Rather than presenting an exhaustive review of relevant research, we will briefly mention several lines of investigation that may suggest useful hypotheses for our own work (see Exhibit 5).

A large literature deals with the impact of "knowledge of results" (KR) on motor learning and performance (Adams, 1987; Salmoni, Schmidt, & Walter, 1984). Researchers have studied how behavior on motor tasks is affected by such KR variables as absolute and relative frequency, temporal locus, and precision. In seeking to explain why knowledge of results influences motor behavior, investigators have emphasized its motivational, as well as associational and guidance, functions (e.g., Strang, Lawrence, & Fowler, 1978).

The effect of feedback on conceptual learning has also been studied. For example, it has been found that children perform better on discrimination-learning tasks when they receive verbal or symbolic feedback rather than tangible feedback (Barringer & Gholson, 1979) and when they receive punishment (either alone or with reward) rather than reward alone (Getsie, Langer, & Glass, 1985). Both of these effects are presumably due, at least in part, to motivational factors. Other research designed to investigate how feedback affects academic performance has indicated that students do better when they take graded as opposed to pass-fail courses (Gold, Reilly, Silberman, & Lehr, 1971), when their homework is checked (Austin, 1978), and when their parents are frequently informed about their progress (Barth, 1979). Research with adults has found that (a) in mathematics learning, the type of feedback that subjects attend to (positive vs. negative) affects performance (Tomarken & Kirschenbaum, 1982), (b) in military training involving electronics, propulsion engineering, and teletype use, provision of detailed performance feedback facilitates learning, especially when the feedback is given on demand and shows the incentives available for different performance levels (Hamovitch & Van Matre, 1981; Van Matre, Pennypacker, Hartman, Brett, & Ward, 1981) and (c) in multiple-cue probability learning, certain forms of computer graphic feedback increase learning on complex tasks (Hoffman, Earle, & Slovic, 1981).

Feedback and performance have also been investigated in organizational settings. Ilgen, Fisher, and Taylor (1979) have suggested that the effect of feedback on performance is mediated by the recipient's perception of the feedback, acceptance of the feedback, desire to respond to the feedback, and intended response (or goals). Each of these mediators, in turn, is influenced by several additional variables. For example, potentially important determinants of the recipient's perception of feedback include the timing, valence, and frequency of the feedback.

The importance of goals in determining motivation and performance, and the joint impact of feedback and goals, have been emphasized by many authors. Mento, Steel, and Karren (1987) report the results of a meta-analysis that supports Locke's (1968) contention that hard goals (if accepted) lead to higher performance than do easy goals ($\underline{d}$ = .58) and that specific hard goals lead to higher performance than do general goals ($\underline{d}$ = .44). These reviewers also found that the efficacy of specific hard goals was increased by the use of

feedback (see also Locke, Shaw, Saari, & Latham, 1981). In related work, Bandura and Cervone (1983) found that task motivation was highest when both performance goals and feedback were present. Additional research suggests that proximal and distant goals can have different effects on motivation (Manderlink & Harackiewicz, 1984).

Other investigators have focused on how feedback can influence goal setting. Work on "level of aspiration" indicates that negative performance feedback causes individuals to lower their expectations for future performance, whereas positive feedback causes individuals to raise their expectations (e.g., Lewin, Dembo, Festinger, & Sears, 1944). Moreover, consistent with the idea that interpersonal as well as intrapersonal feedback is important, evidence indicates that individuals' assessments of their performance quality are affected by how others perform (e.g., Anderson & Brandt, 1939; Chapman & Volkmann, 1939; Dreyer, 1954; Gerard, 1961; Fontaine, 1974).

A huge literature exists on achievement motivation, and many controversies rage regarding its causes and consequences. Nevertheless, most achievement motivation research is based on some version of expectancy-value theory and assumes that performance feedback plays an important role in influencing expectancies (e.g., Atkinson & Feather, 1966; Dweck & Elliott, 1983; Feather, 1982; Kanfer, 1987; Trope, 1986). Attributional and learned helplessness models of achievement motivation, which focus on cognitions about success and failure, give particular emphasis to the impact of feedback on expectancies (Dweck & Goetz, 1978; Weiner, 1986).

The utility of different *types* of feedback has been of interest to many motivational theorists. Dweck and Elliott (1983) and Nicholls (1984) have argued that intrapersonal and interpersonal feedback are differentially important depending on the particular achievement goal (learning vs. performance) that is dominant. Researchers who study intrinsic motivation have suggested that different forms of feedback (e.g., performance-contingent vs. task-contingent) have different effects on subjects' interest in the task (Harackiewicz, Sansone, & Manderlink, 1985; Lepper, 1983; Sansone, 1986). And, Trope (1986) has suggested that the "diagnosticity" of performance information (i.e., the degree to which the information reveals an underlying ability) is a crucial determinant of achievement striving. According to this analysis, a person is motivated to work on tasks that have a high probability of providing the kind of ability information that he or she seeks (self-enhancing information; accurate information).

We will conclude this overview by briefly mentioning some social psychological research on how people react to intrapersonal and interpersonal performance information. While this work is typically not couched in motivational terms, it is nevertheless relevant to our present concerns. In regard to the impact of *intrapersonal* feedback, studies have indicated that the pattern and variability of subjects' performance on a task influence their liking for the task, their attributions for their performance, and their degree of task persistence (e.g., Bryant & Perloff, 1986; Chaiken, 1971; Harvey & Kelley, 1974). In regard to the impact of *interpersonal* feedback, studies have revealed a wide range of cognitive, affective, and behavioral reactions. Learning that one's performance is superior or inferior to that of another has been found to influence attributions for past performance, expectancies for

future performance, affective reactions, amount and quality of task-related behavior, and self-reward (Levine, 1983). Moreover, there is reason to believe that the outcomes of comparison may vary depending on whether two individuals are members of the same group or different groups and whether comparisons are made at the individual level or the group level (Levine & Moreland, 1986, 1987, 1989; Rjisman, 1974, 1984).

The Present Project

Research Questions

The studies reviewed above, though relevant to our concerns, do not explicitly investigate the motivational consequences of intrapersonal and interpersonal performance feedback on cognitive tasks that require substantial practice. In order to clarify these consequences, it is necessary to investigate questions such as the following:

- When the subject receives intrapersonal feedback alone
  - What is the optimal way to aggregate absolute performance information to enhance learning?
    - Last trial only
    - Moving average for last n trials
    - Weighted average for all trials in block (e.g., recent trials weighted most heavily)
    - Unweighted average for all trials in block (all trials weighted equally)
  - What is the optimal way to "grade" performance information to enhance learning?
    - Absolute standard (e.g., 95% = A, 90% = B, etc.)
    - Stable performance-based standard (criteria derived from S's initial performance, e.g., 20% above mean = A, 10% above mean = B, mean = C, etc.)
    - Moving performance-based standard (criteria derived from S's continuing performance, e.g., 20% above mean of last 5 trials = A, 10% above mean of last 5 trials = B, last trial = C, etc.)
    - Normative standard (criteria based on performance of other Ss)
  - To what extent is learning in Trial Block n associated with:
    - Performance expectation for Block n
    - Discrepancy between performance expectation for Block n-1 and actual performance in Block n-1

- Attribution(s) for performance in Block n-1
- Satisfaction with performance in Block n-1

- When the subject receives both intrapersonal and interpersonal feedback

  - What factors optimize learning under individual competition?

    - Self and other similar or different in initial skill level
    - Trial-by-trial feedback about self and other voluntary or obligatory
    - Feedback available to self only or to both self and other
    - Anticipation or no anticipation of future competition

  - What factors optimize learning under group competition?

    - All above issues for individual competition
    - Self and other compete as team representatives or entire teams compete
    - In team case, all members of one team perform before all members of other team or members from two teams alternate
    - In team case, all members perform same task or different tasks
    - In team case, performances of individual members are private or public within and between teams

Studies on Intrapersonal Performance Feedback

Our initial work dealt with the impact of intrapersonal performance feedback. We have conducted several experiments designed to develop our research paradigm and provide preliminary information about how intrapersonal feedback affects motivation and learning. Our research was guided by the assumption that the informativeness of feedback is a crucial determinant of motivation. We believe that informativeness depends on the following factors:

- Interpretability (use of a known metric for describing performance)
- Degree of covariation with performance
- Sensitivity
- Timeliness in tracking performance
- Responsiveness to "significant" changes in performance

Study 1. The purpose of this initial study was to assess the impact of reaction-time (RT) feedback and a self-evaluation "probe" question on performance in a category-search task. The probe question was designed to measure one of the psychological factors that might

mediate the effect of performance feedback on learning. Because we wanted to include probe questions in subsequent studies, we needed to determine whether merely answering such questions would affect subjects' task performance.

Four conditions were used in which subjects received accuracy feedback after each trial (see Exhibit 6). In the No RT/No Probe condition (n = 10), RT feedback was not presented, and subjects were not asked the probe question at the end of each block of trials. In the RT/No Probe condition (n = 10), subjects received RT feedback after each correct trial, but were not asked the probe question. In the No RT/Probe condition (n = 12), subjects did not receive RT feedback, but were asked the probe question. And, in the RT/Probe condition (n = 10), subjects both received RT feedback and answered the probe question. Subjects were college students who were paid $4.00 for their participation in the study.

The category-search task was presented using the Microcomputer Experimental Laboratory (MEL), which runs on IBM-compatible microcomputers. Subjects were shown pairs of category labels, such as "article of clothing" and "musical instrument," followed by two target words, such as "shirt" and "rifle." The subject's task was to respond "yes" if either target word belonged in either category and to respond "no" otherwise. The subject initially completed 12 practice trials (on which only accuracy feedback was presented) and then used 9-point scales to answer several questions about the task, including his level of probable performance, his attributions for future task success/failure (effort, ability, luck, task difficulty), and his view of how enjoyable and challenging the task would be. Next, the subject completed 14 blocks of 48 trials each. On all trials, target words were variably mapped onto category labels (i.e., a given target word was correct on some trials and incorrect on other trials). After each response, the subject received accuracy feedback (the word "correct" or the word "error" accompanied by the type of error). In addition, if he was in an RT condition, the subject also received reaction-time feedback (in milliseconds) after each correct response. After each block of trials, subjects in the Probe conditions were asked to rate their performance on a 9-point scale. After Blocks 7 and 14, subjects in all conditions answered questions that were very similar to those they had answered after the practice trials. All responses were stored by the computer. Following the experiment, subjects were told the purpose of the study and any questions were answered. The entire procedure took about one hour.

Analyses were conducted on subjects' response latency and response accuracy. Results revealed significant RT effects on both dependent measures. Across the 14 blocks of trials, subjects who received RT feedback had shorter response latencies (when they answered correctly) (M = 1219 msec.) then did subjects who did not receive RT feedback (M = 1563 msec.). In contrast, subjects who received RT feedback were less accurate (M = .88) than were subjects who did not receive RT feedback (M = .92). These data suggest a speed-accuracy trade-off. In addition, response latencies decreased over blocks of trials. The absence of other effects suggested, as hoped, that the inclusion of the probe questions did not affect subjects' performance on the category-search task.

Several correlational analyses were conducted to clarify the relationships between (a) subjects' latency and accuracy scores and (b) subjects' answers on the probe and other

questions. We attempted to determine, for example, if subjects' attributions for their performance were related to the quality of their performance and if these relationships differed as a function of the type of feedback that subjects received. These analyses did not yield any easily interpretable patterns of results.

Study 2. In contrast to Study 1, which used feedback from only the previous trial, Study 2 assessed the impact of feedback aggregated across trials. More specifically, we investigated how learning in a category-search task was affected by four types of RT feedback (see Exhibit 7). These RT variations were (1) Last Trial Only (similar to the RT conditions of Study 1 - Exhibit 8), (2) Unweighted Average (based on all preceding trials in the block, weighted equally - Exhibit 9), (3) Weighted Average (based on all preceding trials in the block, with recent trials weighted more heavily than earlier trials - Exhibit 10), and (4) Moving Average (based on the most recent 16 trials in the block, weighted equally - Exhibit 11). As in Study 1, subjects in all conditions received accuracy feedback after each trial. In addition, probe questions were presented after each block of trials in all conditions. Thirteen college students served as subjects in each of the four conditions. Subjects received $5.00, as well as course credit, for their participation.

We expected that the different types of feedback would vary in informativeness, which in turn would affect subjects' learning. Specifically, we predicted that feedback informativeness and therefore learning would be highest in the Weighted Average condition, next highest in the Unweighted Average condition, and lowest in the Moving Average and Last Trial Only conditions.

The experimental task was the same as that used in Study 1, with a few exceptions. Rather than completing 12 practice trials followed by 14 blocks of 48 variably-mapped (VM) trials, subjects initially completed 3 blocks of 60 VM practice trials, followed by 14 blocks of 60 consistently-mapped (CM) trials (in which a given target word was always correct or always incorrect). Moreover, rather than answering only one probe question after each block of trials, subjects answered six questions. Using 7-point scales, subjects evaluated their performance on the current block, evaluated their performance on the current block relative to the previous block, rated the informativeness of the performance feedback received on the current block, rated their effort on the current block, predicted their performance on the next block relative to the current block, and rated their confidence in this prediction. Following the last block of trials, subjects answered 10 questions dealing with perceived changes in their accuracy and RT over blocks of trials, attributions for their performance, their enjoyment of the task and its degree of challenge, and the amount of attention that they paid to accuracy and RT feedback. Finally, subjects were asked to draw graphs of the changes in their response time and accuracy over the 14 blocks of trials. The experimental session lasted approximately 1.5 hours.

The results revealed several interesting trends. Subjects increased their response accuracy and decreased their response latency over blocks in all conditions. In addition, accuracy was lower in the Weighted Average condition ($\underline{M}$ = .84) than in the remaining three conditions ($\underline{M}$ = .92). Recall that we predicted that RT feedback would be most informative in the Weighted Average condition. If so, then subjects' reliance on RT feedback in this

condition may have caused them to pay less attention to accuracy feedback. Subjects in the Weighted Average condition had relatively short response latencies (on correct trials) ($\underline{M}$ = 793 msec.), suggesting that they used the RT feedback that they were provided. Moreover, in responding to post-experimental questions, subjects in the Weighted Average condition reported that they paid less attention to accuracy feedback ($\underline{M}$ = 2.77) than did subjects in the three other conditions ($\underline{M}$ = 4.18). Response latencies in the Unweighted Average condition ($\underline{M}$ = 807 msec.) were almost as short as those in the Weighted Average condition, indicating that subjects were able to derive information from RT feedback that was averaged over the entire block of trials. Subjects in the remaining two conditions (Moving Average and Last Trial Only) showed somewhat longer response latencies ($\underline{M}$s = 867 and 857 msec., respectively).

Other data obtained in Study 2 were also of interest. For example, a positive correlation was obtained between subjects' actual and "graphed" response latencies across the four conditions ($\underline{r}$ = .58), indicating that subjects were sensitive to block-by-block trends in their response latencies. The correlation between subjects' actual and graphed accuracy scores was much weaker ($\underline{r}$ = .19). In addition, subjects in the Weighted Average condition reported expending somewhat less effort on the task (particularly in the later blocks) than did subjects in the other three conditions ($\underline{M}$ = 4.20 vs. $\underline{M}$ = 5.49). In examining subjects' block-by-block judgments of the informativeness of performance feedback, we did not find clear parallels between how useful RT feedback was judged to be and how much it actually influenced accuracy and response latency. This suggests that subjective judgments of feedback informativeness may not always be a good indicator of the effectiveness of feedback. Finally, in extensive block-by-block analyses exploring relationships between actual performance, evaluations of past performance, and expectations for future performance, few reliable relationships were obtained.

<u>Study 3.</u> In this and the following experiments, we shifted from a category-search task to an electronic trouble shooting task. This latter task has more real-world training implications. In this study, our goal was to adapt an existing trouble shooting task to the MEL environment and to gather data regarding the impact of several types of RT feedback. In addition to Last Trial Only, Unweighted Average, and Weighted Average feedback, we included a fourth condition in which subjects received "graded" feedback (Exhibit 12). As in Studies 1 and 2, subjects received accuracy feedback after each trial and answered probe questions after each block of trials. A within-subjects design was used in which six college students served as subjects; they were paid a total of $20.00 for five days of participation (one hour/day).

The trouble shooting task was presented using MEL. Subjects were required to predict the output of four kinds of logic gates (and, nand, or, nor), which are basic components of digital circuits. On Day 1, subjects first received a written introduction to digital electronics that described fundamental aspects of logic gates and truth tables. Then, they were given 192 practice trials on logic gates; accuracy feedback was provided on each trial. In each of three sets of 64 trials, subjects worked on 16 consecutive examples of each of the four gate types. During these practice trials, subjects had access to a "help" key that showed the truth table for the current trial. Finally, subjects were given 48 trials in which the four gate

types were intermixed and the help key was not available. Performance on the final 48 trials was used to screen subjects for further participation. Only subjects who were correct on at least 75% of these trials were retained.

On each of the following three days (Days 2, 3, and 4), subjects received one type of RT feedback -- Last Trial Only, Unweighted Average, or Weighted Average. The order of the three types of feedback was counterbalanced across subjects. On each day, subjects were given four blocks of 144 trials; each block contained 36 (intermixed) examples of each gate type. Accuracy feedback consisted of either the word "correct" or the word "error." RT feedback was given in milliseconds. After each block of trials, subjects were asked to estimate the number of errors that they made and their typical response latency on the current block of trials and to predict number of errors and typical response latency on the next block. Following the fourth block of trials, subjects used 7-point scales to answer 10 questions dealing with perceived changes in their accuracy and response latency over blocks of trials, attributions for their performance, their enjoyment of the task and its degree of challenge, and the amount of attention that they paid to accuracy and RT feedback.

On Day 5, subjects initially completed a transfer task in which they were asked to trouble shoot 32 miniature circuits, each containing two sets of three gates. Next, subjects received training on individual gates with "graded" RT feedback. Subjects were given four blocks of 64 trials; each block contained 16 (intermixed) examples of each gate type. After each trial, subjects received accuracy feedback and a special form of Last Trial Only RT feedback. They were shown RT in milliseconds, normalized by the typical performance of all subjects on the relevant gate type, as well as a grade label (awful, poor, below average, average, above average, good, or excellent). The label was based on the difference between the subject's current response latency and his average latency at the end of Day 4 (Exhibit 13). Following each block of trials, subjects received cumulative feedback regarding their average accuracy on that block, their average response latency, and their average response-latency grade. After they saw the cumulative feedback, subjects indicated their difficulty in concentrating during the current block of trials and predicted their accuracy and typical response latency during the next block. Finally, subjects completed the same 10 questions that they had answered at the end of Days 2, 3, and 4.

A substantial amount of effort was expended in adapting the electronic trouble shooting task to the MEL environment. This effort was worthwhile in that subjects showed substantial training effects within and between Days 2, 3, and 4 and performed well on the transfer task on Day 5. On Day 2, subjects' accuracy improved over the four blocks of trials. Mean accuracy (across the three RT feedback conditions) rose from 87% on Block 1 to 96% on Block 4. This latter accuracy level was maintained during Days 3 and 4. Regarding response latency, subjects' latency decreased over blocks of trials on each day of training. In addition, average response latency decreased across Days 2, 3, and 4 ($\underline{M}$s = 1685, 883, and 745 msec., consecutively). These effects occurred regardless of the type of RT feedback (Last Trial Only, Unweighted Average, Weighted Average) that subjects received.

In regard to the questions that subjects answered concerning their current and future performance, no significant effects due to feedback type were obtained. It is interesting,

however, that regardless of the type of feedback they received, subjects were quite accurate in estimating their current accuracy (mean actual - estimated number of errors = 1.50) and response latency (mean actual - estimated RT = -28.67 msec.). This suggests that the three types of feedback were equally informative, which may help to explain why feedback type failed to influence subjects' performance.

The graded RT feedback on Day 5 was included to provide preliminary information concerning how well-trained subjects would respond to performance feedback (both trial and block) that was explicitly evaluative. Results indicated that subjects continued to maintain over 90% accuracy during Day 5, while at the same time decreasing their response latency across blocks. In addition, during post-experimental interviews, the majority of subjects reported that they preferred the graded feedback to the three other types.

Study 4. In this experiment, we used a larger, between-subjects design to assess the impact of the four types of performance feedback investigated in Study 3 (Last Trial Only, Unweighted Average, Weighted Average, Graded Last Trial Only). Ten college students served as subjects in each of the four conditions. Subjects received a total of $8.00 for two days of participation (one hour/day).

The experimental task was the same as that used in Study 3, with a few exceptions. Subjects participated in two, rather than five, sessions. On Day 1, subjects again completed practice trials on the four gate types separately (with access to a help key) and then completed a series of mixed trials (without the help key). Only subjects who answered correctly on 75% or more of the mixed practice trials were retained. On Day 2, subjects in each of the four RT feedback conditions completed four blocks of 144 trials and received accuracy and response latency information. Feedback in the Last Trial Only, Unweighted Average, and Weighted Average conditions was identical to that in Study 3. Feedback in the Graded Last Trial Only condition differed from that in Study 3 in one minor way: Labels were based on the difference between the subject's current response latency and the average latency of previous subjects with a similar amount of training on the same task. After each block and at the end of the final block, subjects answered the same questions as in Study 3.

Subjects in all conditions showed significant increases in accuracy and decreases in response latency across blocks of trials. In addition, response latencies were somewhat shorter in the Last Trial Only and Graded Last Trial Only conditions (Ms = 1198 and 1156 msec., respectively) than in the Unweighted Average and Weighted Average conditions (Ms = 1478 and 1316 msec., respectively). This pattern of findings was different from that obtained in Study 2, where latencies were somewhat shorter in aggregated-feedback than in nonaggregated-feedback conditions, suggesting that task type may influence the impact of different forms of performance feedback.

Conclusion. The results of these studies indicated that we created an appropriate experimental situation for investigating the learning of component skills. We found, for example, that feedback affected performance even with the relatively short practice periods that we employed. In Study 1, where subjects worked for less than an hour, subjects who

received RT feedback had shorter response latencies than did those who did not receive this type of feedback. In addition, as hoped, the inclusion of probe questions did not affect subjects' performance, indicating that we can use these questions without concern that they will bias other measures. In all four studies, reasonable power-law practice functions were obtained on response latencies, suggesting that learning was occurring in a normal fashion. Examination of the relationship between subjects' actual response latencies and recalled latencies in Studies 2 and 3 revealed that subjects were paying attention to the RT feedback that they received. Finally, there was some evidence that subjects liked the graded feedback better than the other forms of feedback in Studies 3 and 4.

In contrast to the optimistic picture portrayed by the above findings, other data were less encouraging. We did not find strong or consistent RT differences between feedback conditions, and few reliable relationships were obtained between current performance and either evaluations of past performance or expectations for future performance. Our failure to find stronger effects may have been due to the relatively short practice periods that we provided. As mentioned earlier, motivational problems on tasks like the ones we used often do not arise for hundreds or thousands of trials. Since our subjects only worked for an hour or two and were still improving at the end of the experiment, they may have been unresponsive to feedback differences that would influence the performance of less-motivated learners.

Studies on Intrapersonal and Interpersonal Performance Feedback

In these studies, students received information about temporal trends in both their own and others' performance. Several authors have suggested that competition between individuals generally has deleterious effects on task motivation and performance (e.g., Ames, 1984; Johnson, Maruyama, Johnson, Nelson, & Skon, 1981; Slavin, 1983). Others have questioned this conclusion, suggesting that under certain circumstances competition can stimulate effort and learning (e.g., Ball, 1984; Cotton & Cook, 1982; Levine, 1983; Michaels, 1977; Seta, 1982). The goal of our research was to assess how joint intrapersonal and interpersonal performance feedback, which is essential to competition, affects the acquisition of component skills that require substantial practice.

Study 5

In this experiment, we used a between-subjects design to assess the joint impact of intrapersonal and interpersonal feedback. Fourteen college students served as subjects in each of the four conditions. Subjects received a total of $8.00 for two days of participation (one hour/day).

The experimental task was basically the same as that used in Study 4. On Day 1, subjects again completed practice trials on the four gate types separately (with access to a help key) and then completed a block of mixed trials (without the help key). Only subjects who answered correctly on 75% or more of the mixed practice trials were retained. On Day 2, subjects in each of the four performance feedback conditions completed eight blocks of

64 trials and received accuracy and response latency information. At the end of every third block of trials and after the last block, subjects answered the same questions as in Study 4.

The performance feedback that subjects received differed from our previous studies in two major ways. First, subjects were given cumulative feedback at the end of each block of trials. This cumulative feedback was based on a roughly equal composite weighting of the subject's mean accuracy and mean response latency on the current block of trials. Feedback scores were computed using the formula: score = (minimum RT/mean RT) X mean accuracy. Minimum RT was based on pilot data. In addition, subjects received information about temporal trends in both their own and others' performance on the task. Four types of performance feedback were investigated, using the electronic trouble shooting task. In each condition, subjects were shown their composite performance score at the end of each block of trials, followed by a graph of their composite scores for all of the blocks completed up to that point.

In the Self-Only (control) condition, subjects saw only their own performance scores on the graph (see Exhibit 14). In the three experimental conditions, subjects' graphs included both their own (veridical) performance scores and the (manipulated) performance scores of the "average person with the same amount of experience on the task." This average other's performance scores were either similar to, worse than, or better than the subject's performance scores. In the Self-Equal condition, subjects saw the scores of an average other who performed at approximately the same level as they did (see Exhibit 15). In the Self-Superior condition, the average other's performance was consistently and progressively worse than the subject's performance over blocks (see Exhibit 16). Finally, in the Self-Inferior condition, the average other's performance was consistently and progressively better than the subject's performance over blocks (see Exhibit 17). In each experimental condition, the average other's performance was based on predetermined deviations from the subject's own performance.

Subjects' responses to the post-test questions (answered using 7-point scales) suggested that our feedback manipulation was successful. Subjects in the Self-Inferior condition rated their overall performance as worse than that of the average other ($\underline{M}$ = 2.00), whereas subjects in the Self-Superior condition rated their overall performance as better than that of the average other ($\underline{M}$ = 5.64). Subjects in the Self-Equal and Control conditions rated their performance as approximately equal to that of the average other ($\underline{M}$s = 4.00 and 4.21, respectively). Across the four feedback conditions, subjects in the Self-Inferior condition were the least pleased with their performance ($\underline{M}$ = 3.29), whereas subjects in the Self-Superior condition were the most pleased with their performance ($\underline{M}$ = 4.79).

Subjects in all conditions showed increases in accuracy and decreases in response latency across blocks of trials. In addition, analysis of subjects' composite performance scores showed increases across blocks of trials in all conditions. However, the four types of performance feedback did not produce reliable differences in composite scores, perhaps because subjects worked for a relatively short period of time (two hours).

Study 6

This experiment differed from Study 5 in several important ways. First, to assess how intrapersonal and interpersonal feedback affect performance when motivational problems are more likely to be serious, we had subjects work on electronic troubleshooting tasks for relatively long periods of time (i.e., five hours, as compared to two hours in Study 5). Second, rather than having subjects work on the same electronic components day after day, we introduced new components on successive days, as would occur in a real training environment. Third, in order to increase the realism of the task even further, we had subjects learn complex electronic devices as well as simple logic gates. Finally, we assessed how subjects' level of achievement motivation affected their responses to various types of performance feedback.

Sixty-three undergraduates participated in five one-hour sessions, held on five consecutive days. Subjects were screened to eliminate engineering students and people familiar with electronics. Subjects were randomly assigned to the five conditions (four experimental and one control) and paid $22.00 for their participation.

The experimental task involved learning a set of 24 electronic components drawn from the 7400 TTL logic series. These components are the core modules of digital circuitry and must be learned before an individual can do electronic trouble shooting. Subjects were required to predict the outputs for each of 24 components. These components included eight simple logic gates (Exhibit 18) and 16 complex devices (Exhibit 19).

Pilot research was conducted to determine the difficulty of learning each of the 24 components. Based on this research, the components were divided into four sets of six components each that were approximately equal in difficulty. Each set contained two logic gates and four devices. The first two days of the experiment were designed to familiarize subjects with the task and allow them to acquire basic proficiency with a few components. On both of these training days, subjects worked on the same set of six components. The last three days of the experiment were designed to determine how various types of performance feedback influenced subjects' performance. On each of these experimental days, subjects worked on a different set of six components.

On Day 1 subjects were initially asked to complete the Achievement subscale of Jackson's (1984) Personality Research Form. This 16-item scale, which assesses individual differences in achievement motivation, has been shown to possess high reliability and validity. Example of items are "I enjoy difficult work" and "When I hit a snag in what I am doing, I don't stop until I have found a way to get around it." Next, subjects received a written introduction to digital electronics in order to familiarize them with the task. This introduction briefly described the difference between digital and analog electronic circuits, what it means to code information digitally, the operations that electronic components perform on binary-coded information, and how to read a truth table. In addition, subjects were given a handout containing the truth tables for the six components that they would be learning on Day 1 (Exhibit 20).

After the, had an opportunity to study the truth tables and ask questions about them, subjects received additional instructions on the computer. These instructions informed subjects that their job was to learn the relationships between inputs and outputs for the six electronic components they had just studied. They were informed that, if they had trouble with any component, they could press the "help" key on their keyboard and see the truth table for that component on the screen. Finally, subjects were told that they would see either the word "correct" or the word "error" after each trial. After receiving all of these instructions, subjects completed 144 practice trials, during which they responded to 24 examples of each of the six components.

At the end of the practice trials, subjects read instructions for the remaining test trials. Subjects were told that on the test trials examples of the six kinds of components would be mixed together and the help key would be disabled. They were instructed to respond as accurately and quickly as they could and were informed that after each trial they would learn whether they had been correct or incorrect and, on correct trials, how fast they had responded (e.g., 1.55 seconds). They were further informed that at the end of each block of trials, they would receive a single performance score that reflected their combined accuracy and speed on all the trials in the block, and they were shown a table explaining how accuracy and speed were combined to produce these performance scores.

Subjects then completed 12 blocks of 32 trials. Each block contained examples of all six components. After each trial, subjects received accuracy feedback and, if they were correct, response latency feedback as well. At the end of each block of trials, subjects received an overall performance score on that block. These scores, which could range from 0 to 100, were calculated to weight accuracy and speed about equally. Scores were computed using the formula: (.50 ((mean accuracy - minimum accuracy)/accuracy range)) + (.50 (1 - ((mean RT - minimum RT)/RT range))). Minimum accuracy, minimum RT, accuracy range, and RT range were based on pilot data. Performance scores were plotted on a graph, with performance on the Y-axis and block number on the X-axis. In this way, subjects saw a cumulative record of their performance over the 12 blocks of trials (Exhibit 21). After every three blocks of trials, subjects rated how pleased they were with their performance on the last three blocks and estimated how well they would score on the next three blocks. After all 12 blocks of trials, subjects answered a series of questions about their reactions to the task (e.g., how much attention they paid to the feedback, how well they performed, how pleased they were with their performance, and why they performed as they had).

The procedures for Day 2 were the same as those for Day 1, except that subjects did not complete the Jackson Personality Research Form and did not receive the written introduction to digital electronics. Therefore, subjects on Day 2 were given an opportunity to study the truth tables from Day 1 and then completed practice and test trials using the same six components that they had worked on before.

The general procedures on Days 3, 4, and 5 were the same as those on Day 2, with two major exceptions. First, a new set of six components was introduced on each successive day beginning with Day 3. The presentation order for the three sets of components was

counterbalanced across subjects within each condition. Second, we introduced our experimental manipulation of performance feedback on Day 3. This manipulation continued on Days 4 and 5.

Subjects in the Grade Band condition saw their performance graphed over a background of five performance curves labeled Excellent, Good, Average, Below Average, and Poor (Exhibit 22). These five performance curves were based on data from pilot subjects -- the Average curve represents the average performance of pilot subjects, and the remaining curves are approximately one or two standard deviations above or below the average performance. Subjects in the Grade Band condition were told that "along with your own performance scores, you will see lines indicating how well you are doing at any point in time. The lines indicate levels of performance that are excellent, good, average, below average, and poor."

Subjects in the Superior Other, Average Other, and Inferior Other conditions saw their performance graphed over a background of a single performance curve. In the Superior Other condition, the performance curve was the same as the Excellent curve in the Grade Band condition (Exhibit 23). In the Average Other condition, the performance curve was the same as the Average curve in the Grade Band condition (Exhibit 24). And, in the Inferior Other condition, the performance curve was the same as the Poor curve in the Grade Band condition (Exhibit 25). Subjects in all three conditions were told that "along with your own performance scores, you will see a line indicating the typical performance of previous subjects on this task. This line therefore represents "average" performance."

Finally, subjects in the Control (Self Only) condition did not see any information about grades or others' performance. As on Days 1 and 2, these subjects continued to see a graph displaying only their own performance (Exhibit 26).

In order to interpret the results of the study, it was first necessary to ascertain whether subjects had paid attention to and accurately perceived the performance feedback that they received. We therefore examined subjects' responses to the post-experimental questions that they answered at the end of Days 3, 4, and 5. To the question, "How much attention did you pay to the performance feedback graph at the end of each block?", subjects in all five conditions reported a high degree of attention ($\underline{M}$ = 5.94, on a 7-point scale). This level of reported attention, together with the absence of any significant differences between conditions, suggests that subjects did indeed pay close attention to the feedback that they received. Of course, it is possible that subjects' responses to this question simply reflected conformity to demand characteristics, that is, subjects' desire to have the experimenter believe that they followed his instructions.

Fortunately, data on other questions suggest that subjects were in fact attentive to the feedback that they received. On the question, "How do you think your performance compares with the performance of the average person on this task?", a significant condition effect was obtained. Subjects in the Inferior Other condition gave the most positive response, subjects in the Superior Other condition gave the least positive response, and subjects in the Average Other (and two remaining) conditions fell in between (Exhibit 27).

Similar findings were obtained on the question, "How pleased are you with your overall performance on the task?" Here, subjects in the Inferior Other condition were most pleased, subjects in the Superior Other condition were least pleased, and subjects in the Average Other (and two remaining) conditions fell in between (Exhibit 28). It should also be noted that the absence of a significant Day main effect or Condition X Day interaction on responses to this question suggests that subjects did not become suspicious of the veracity of our feedback manipulation as the days progressed.

Finally, the attributions that subjects made for their performance were rather interesting. At the end of each day, subjects were asked to rate the importance of four determinants of their performance: their effort, their ability, their luck, and the difficulty of the task (Exhibit 29). Results indicated that, across conditions, subjects generally gave greater weight to effort and ability (which are internal causes of behavior) than to luck and task difficulty (which are external causes). Moreover, whereas effort and ability were weighted about equally, luck was weighted less heavily than task difficulty.

We then looked at condition differences within attributions and found a couple of interesting patterns. Subjects in the Grade Band and Inferior Other conditions perceived effort to be a somewhat more important determinant of their performance than did subjects in the remaining three conditions. This suggests that subjects in the Grade Band and Inferior Other conditions may have worked harder on the task, or at least viewed themselves as working harder, than did subjects in the other conditions. And, in contrast to subjects in the four other conditions, those in the Superior Other condition viewed ability as a more important determinant of their performance as the days progressed. Since subjects in the Superior Other condition performed relatively poorly compared to the "average" other, their increasing tendency to attribute their performance to (low) ability may have reflected an increasing perception of helplessness, which in turn may have reduced their task motivation.

Let us turn now to a consideration of subjects' performance on the electronic components. We will focus on performance on Days 3, 4, and 5, when the various types of feedback were manipulated. As mentioned earlier, at the end of every block of trials, subjects received a score that reflected their overall performance on the 32 trials in that block. These scores, which could range from 0 to 100, weighted subjects' response accuracy and response speed about equally. On a typical day, over the 12 blocks of trials accuracy scores rose from about 86% to 93%, latency scores fell from about 2200 msec to 1500 msec, and performance scores rose from about 31 to 64 on the 100-point scale. So, by converting to the new metric of performance scores, we not only provided subjects with a "summary" of both their accuracy and speed, but we also made it easy for them to detect rather small changes in their performance.

We adjusted subjects' performance scores on Days 3, 4, and 5 in two ways. First, we used performance on the last block of Day 2 as a covariate to "control" for differences in ability. Second, we omitted subjects' performance on the first block of Day 3, which preceded the introduction of the feedback manipulation.

We initially conducted Condition X Day analyses on both mean performance scores and final performance scores. Both of these analyses failed to yield significant effects, perhaps because the large variability in subjects' responses and the small n per cell made it hard to detect differences. In order to develop a more sensitive index of performance, we computed a difference score for each subject on each day. This score reflected the difference between the subject's performances on the initial and final blocks of trials (Block 12 minus Block 2 on Day 3; Block 12 minus Block 1 on Days 4 and 5).

A Condition X Day analysis on these difference scores yielded a significant Day main effect and a significant Condition X Day interaction. The interaction revealed rather different patterns of performance change in the five conditions (Exhibit 30). As this figure shows, performance difference scores increased substantially over days in two conditions (Grade Band, Inferior Other), but remained relatively stable in the three remaining conditions (Control, Average Other, Superior Other). As days progressed, subjects who received grade feedback or who saw the performance of an inferior other showed larger performance increases from the beginning to the end of the experimental session. This pattern was not exhibited by subjects who saw only their own performance, the performance of a similar other, or the performance of a superior other. Apparently, then, the chance to earn a higher grade or the chance to become even more superior to an inferior other was more motivating than the chance to improve in the absence of either impersonal or personal feedback, the chance to become superior to a similar other, or the chance to become less inferior to a superior other.

Our findings are particularly interesting in light of some of the attributional data presented earlier. Recall that subjects in the Grade Band and Inferior Other conditions were somewhat more likely to attribute their performance to effort than were subjects in the remaining conditions. That subjects in these conditions showed improved difference scores over time may mean that effort attributions facilitated their performance. Although the present methodology does not allow us to establish a firm causal connection between effort attributions and performance, such a relationship is consistent with theory. It is also interesting that subjects in the Superior Other condition, who became increasingly likely to attribute their (relatively poor) performance to (low) ability, did not show improved difference scores over time. Perhaps these ability attributions dampened subjects' motivation to perform. While such an explanation cannot account for the failure of difference scores to rise in the Control and Average Other conditions, there is no a priori reason why the same psychological mechanisms must control behavior under all feedback conditions.

In addition, we might mention the results of correlations between subjects' mean performance difference scores (across Days 3, 4, and 5) and achievement motivation scores in the five conditions. One of these correlations was significant. In the Grade Band condition, subjects who were high in achievement motivation had higher performance difference scores (r = .63). Perhaps the measure of achievement motivation used in this study assesses competition against impersonal standards (such as grade bands) rather than competition against other people (such as inferior others). If so, it might be useful to include a more socially-oriented measure of achievement motivation in future studies, in the hope of identifying an individual difference variable that accounts for some of the variance

in subjects' performance when interpersonal competition is salient.

Assuming that our findings prove to be reliable, one can ask whether Grade Band and Inferior Other feedback are equally useful in real-world training environments. We would tentatively suggest that Grade Band feedback is better suited to such training environments than is Inferior Other feedback. This conclusion is based on the supposition that grade bands are likely to increase motivation for students at all ability levels (except perhaps those who consistently perform poorly), whereas inferior other feedback is only effective if the "average" other is inferior to the student. In real-world training environments, where all students will probably receive veridical information regarding the performance of "average" others, only students who perform at above average or superior levels will see an inferior average other. Students who perform at average, below average, or poor levels will see an average other who is either similar or superior to themselves. And, as our data showed, this type of feedback does not increase students' task motivation.

Conclusion. Studies 5 and 6 both manipulated intrapersonal and interpersonal performance feedback, but yielded rather different results. In Study 5, the various types of feedback did not produce reliable differences in subjects' performance, presumably because of the relatively short practice period that subjects were given (two hours). In contrast, in Study 6, where subjects worked on the task for a longer period (five hours), reliable feedback differences were obtained on a measure of performance improvement within sessions. These results, in conjunction with our earlier findings regarding the impact of intrapersonal feedback alone, suggest that performance feedback is a more powerful determinant of behavior when lengthy practice is needed to produce proficiency. In this context, it is important to note that the differences obtained in Study 6 were based on only three hours of training with performance standards. It is likely that in a normal six-week training course (with 240 hours of instruction), these differences would be magnified. That is, we assume that feedback will become a more powerful motivator as intrinsic interest wanes, which may take a period of time when new components continue to be introduced in successive sessions.

Directions for Future Research

Our work was stimulated by an interest in motivational aspects of computer-based skill training. Because performance feedback has been found to influence learning in a variety of noncomputer environments and because computers provide many opportunities for manipulating such feedback, we embarked on a series of studies designed to assess the motivational impact of various types of intrapersonal and interpersonal feedback. Our work has just scratched the surface of a very complex phenomenon, but we have learned some interesting things about the impact of performance feedback.

Based on our results, we have several suggestions for using performance feedback to enhance motivation in computer based training. As subjects spend more hours with interactive computer based training, motivation becomes a greater problem. Hence, performance feedback of the kinds we used are likely to be more effective in extended training procedures (e.g., greater than 10s of hours of instruction) than in special single-

day enrichment or remedial procedures. Our subjects seemed to like the graphical presentation of their performance over time and the comparison information that they received. The block by block graphical summaries provided visual evidence of continued improvement over time. We found that subjects responded best to Grade Band or Inferior Other comparison data. Since the Inferior Other curves involve deception, they are probably inappropriate for most training environments. We suggest that standard Grade Band subroutines be utilized in multiple lessons. The specific grade band levels need to be established for each lesson individually, taking into account the experience level of students at each stage of instruction.

We believe that future work should be directed toward assessing how individual and group competition affect performance on tasks such as that used in Study 6. The paradigm developed in Study 6 contains several important features o' real-world training environments, including a relatively long practice period (which could be extended even further), the introduction of new components on successive days, the use of complex electronic devices as well as simple logic gates, and the assessment of individual difference factors (e.g., achievement motivation) that are likely to influence performance. In regard to variables that may affect the impact of individual and group competition on performance, we believe that those listed on page 8 are good candidates for initial study.

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Performance Feedback Over Time

- Continuous vs. intermittent
- Constant vs. variable feedback interval (intermittent)
- Performance on last trial or aggregated across set of trials
- Number of trials in set and weighting function (aggregated)
- Absolute vs. relative
- Obligatory vs. voluntary
- Control vs. no control over form of feedback
- Temporal pattern

Exhibit 1

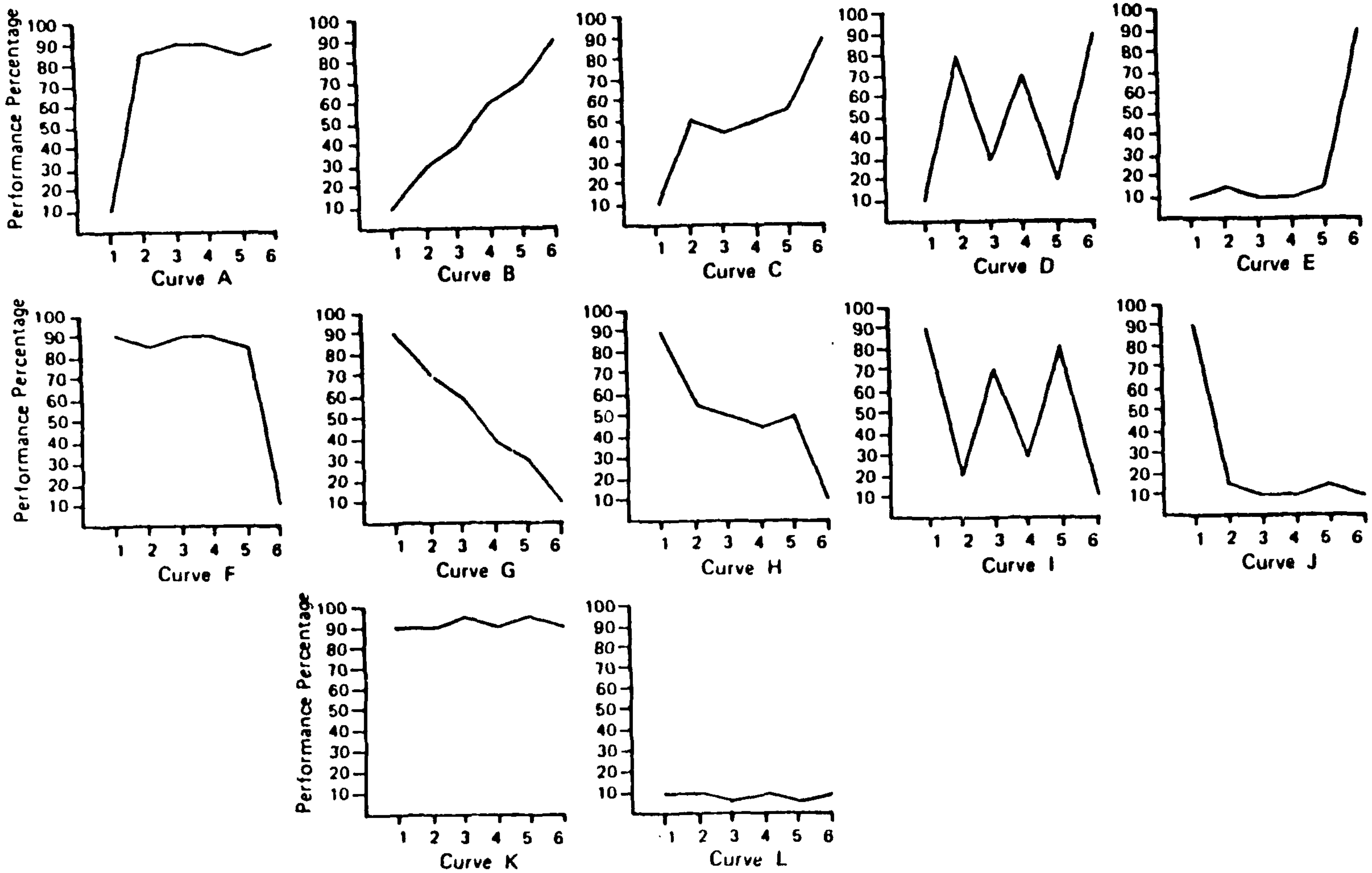
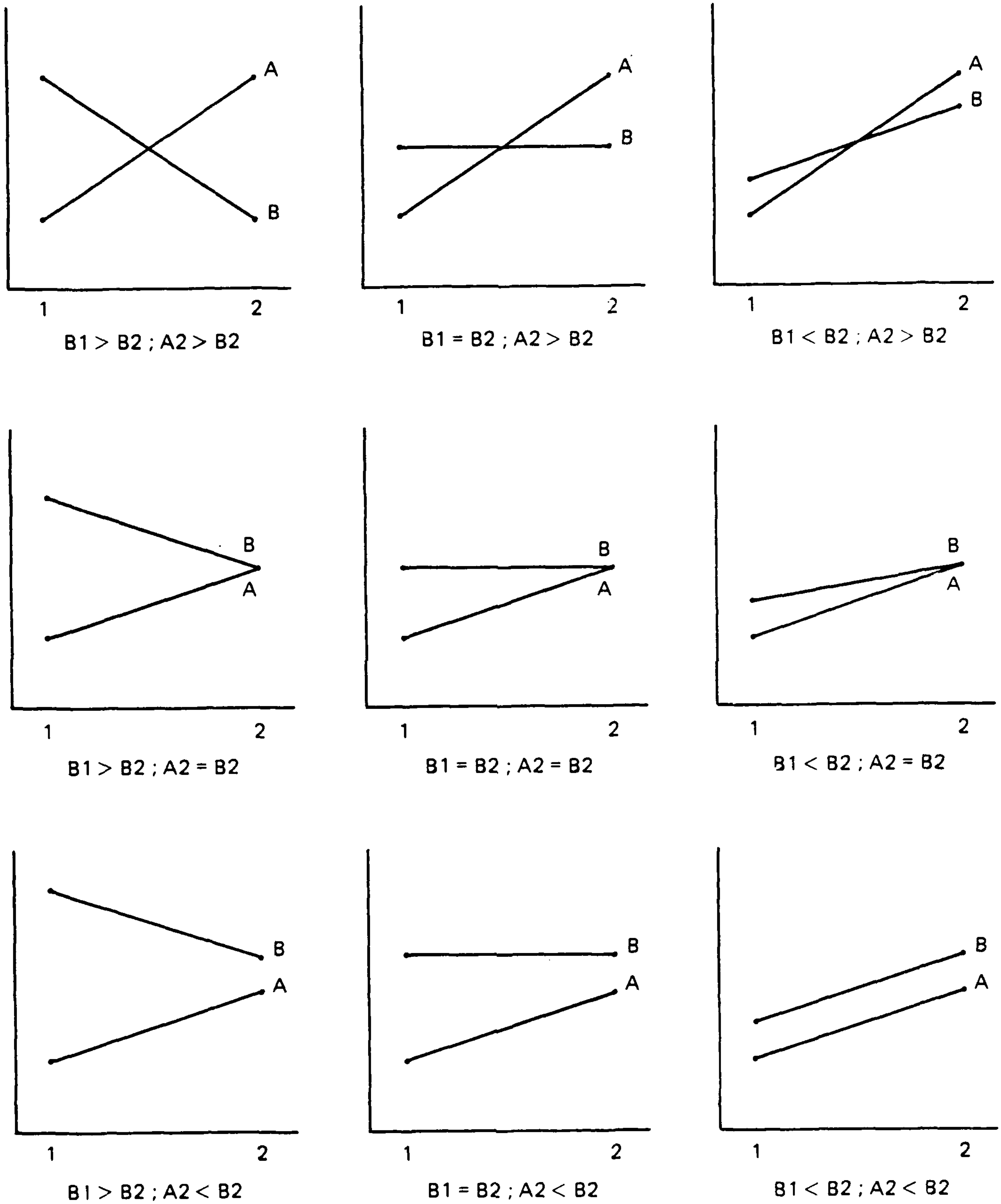

Performance Percentage
100
90
80
70
60
50
40
30
20
10
1 2 3 4 5 6
Curve A
Curve B
Curve C
Curve D
Curve E
Curve F
Curve G
Curve H
Curve I
Curve J
Curve K
Curve L

Exhibit 2

INTRAPERSONAL COMPARISON

INTERPERSONAL COMPARISON		A1 > A2			A1 = A2			A1 < A2		
		B1 > B2	B1 = B2	B1 < B2	B1 > B2	B1 = B2	B1 < B2	B1 > B2	B1 = B2	B1 < B2
A1 > B1	A2 > B2	X	X	X	X	X	X	X	X	X
	A2 = B2	X	X	X			X			X
	A2 < B2	X	X	X			X			X
A1 = B1	A2 > B2	X			X			X	X	X
	A2 = B2	X				X				X
	A2 < B2	X	X	X			X			X
A1 < B1	A2 > B2	X			X			X	X	X
	A2 = B2	X			X			X	X	X
	A2 < B2	X	X	X	X	X	X	X	X	X

Exhibit 3



A1 < A2 ; A1 < B1

Exhibit 4

Relevant Lines of Investigation

- Effect of knowledge of results (KR) on motor learning and performance
- Effect of feedback on conceptual learning
- Feedback and performance in organizational settings
- Goals and feedback as determinants of motivation and performance
- Effect of feedback on goal setting
- Achievement motivation
    - Expectancy-value models
    - Effect of different types of feedback
- Social psychological research on reaction to intrapersonal feedback and joint intrapersonal/interpersonal feedback

Exhibit 5

Study 1

Category-search Task

RT Feedback

		No	Yes
Probe Question	No		
	Yes		

Exhibit 6

Study 2

Category-search Task

Conditions	Last Trial Only Unweighted Average Weighted Average Moving Average

Exhibit 7

LAST TRIAL ONLY

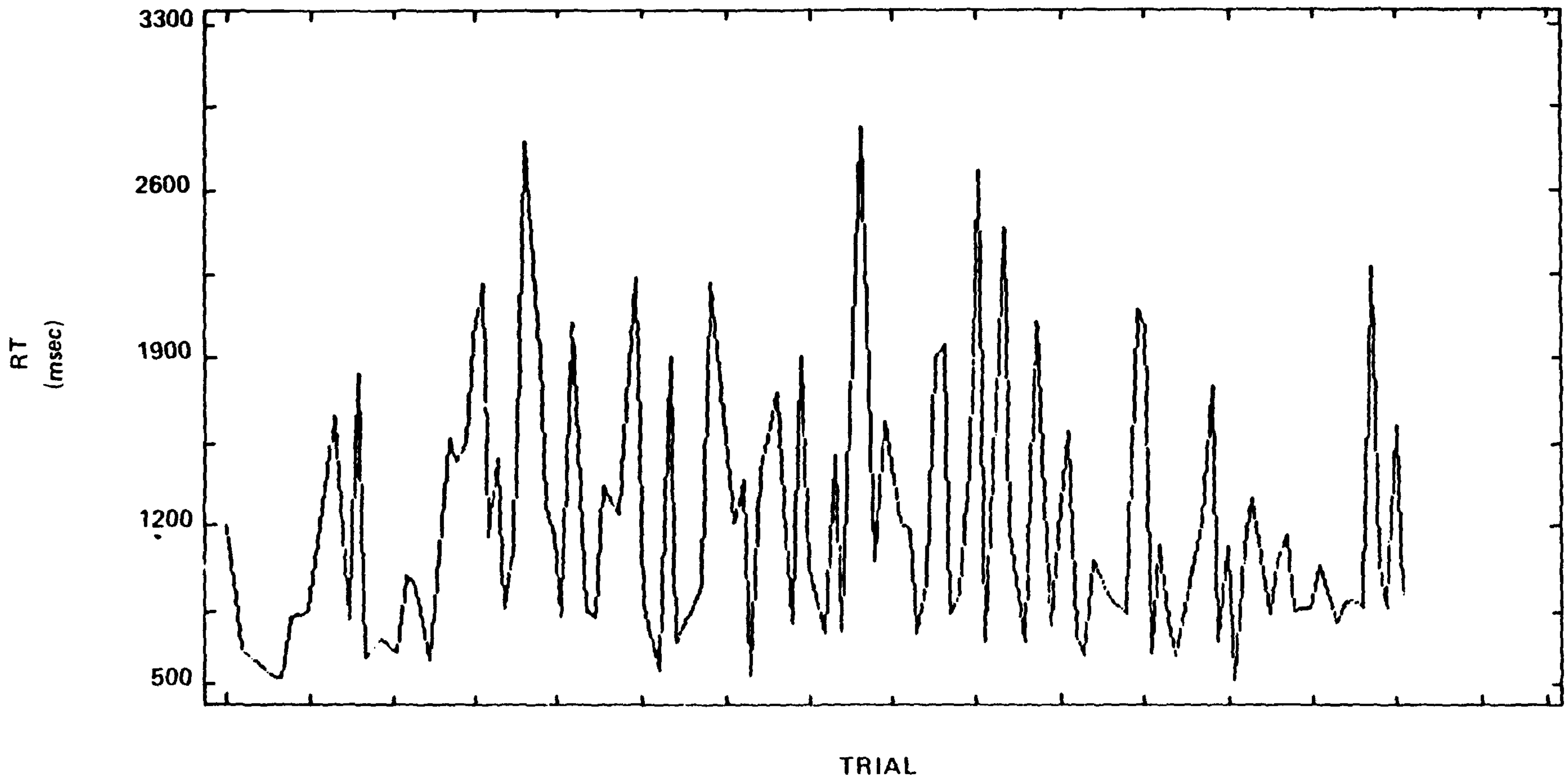


Exhibit 8

UNWEIGHTED AVERAGE

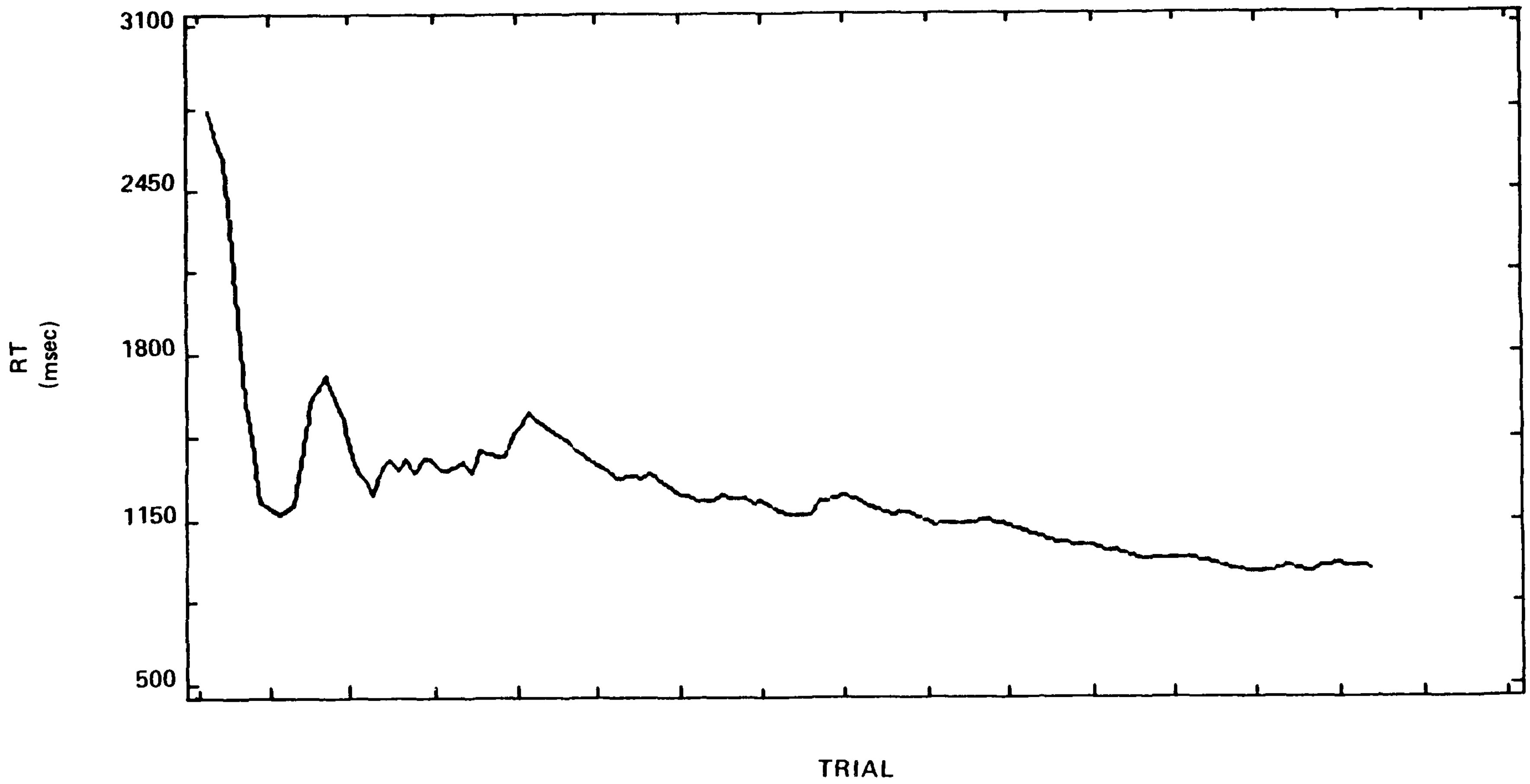


Exhibit 9

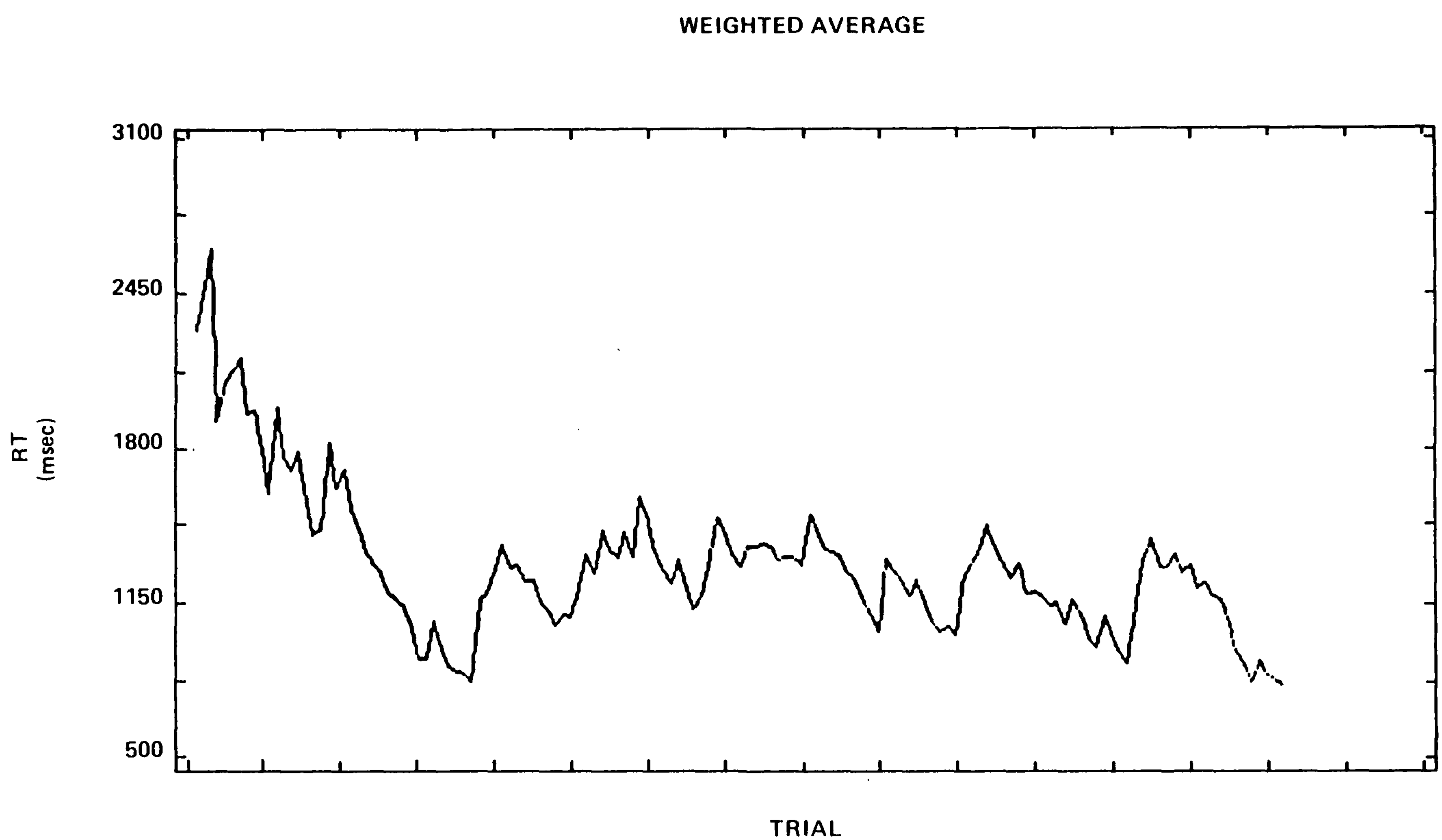


Exhibit 10

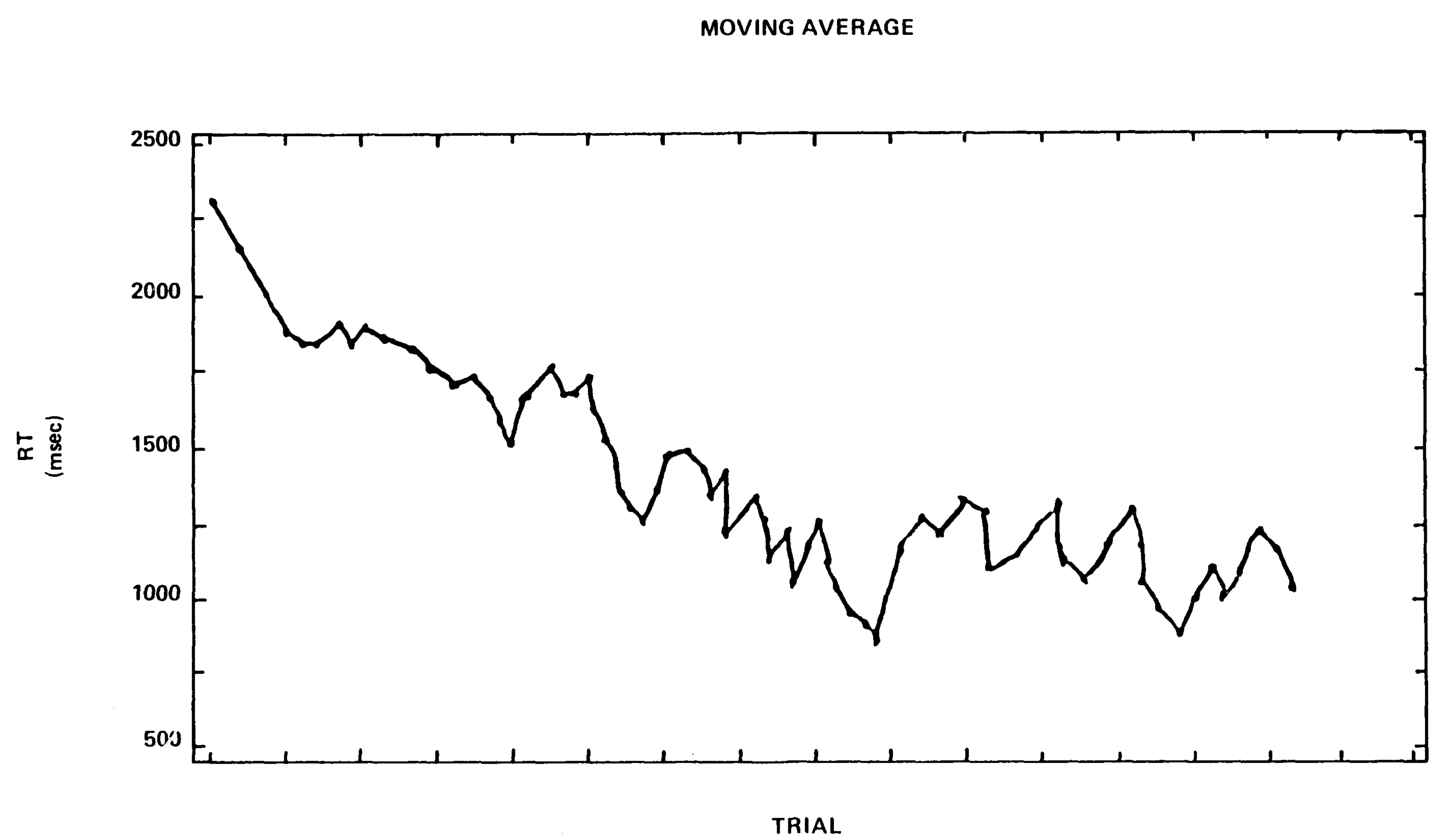


Exhibit 11

Studies 3 and 4

Electronic Trouble-shooting

Conditions

- Last Trial Only
- Unweighted Average
- Weighted Average
- Graded Last Trial Only

Exhibit 12

GRADED LAST TRIAL ONLY

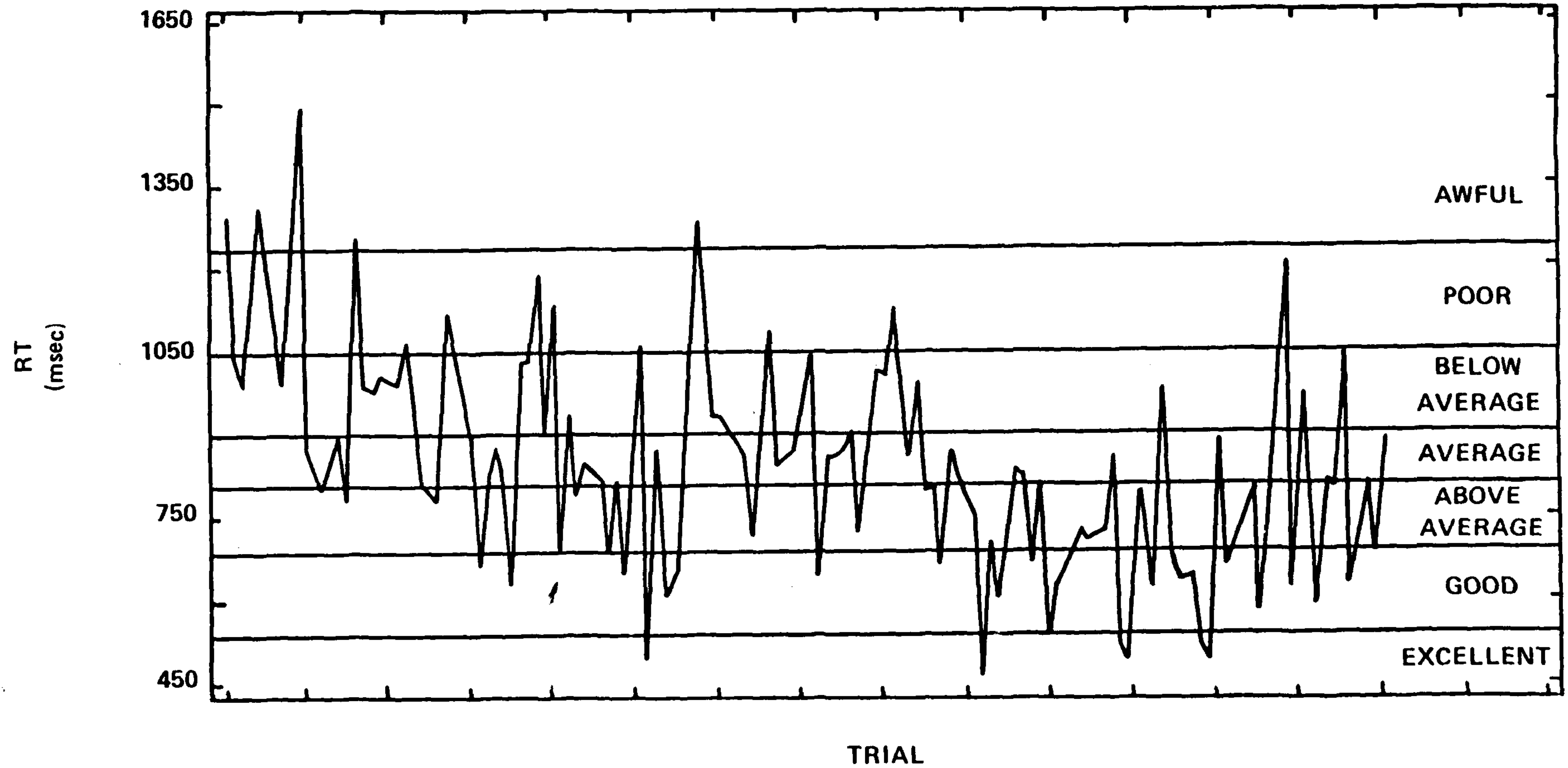


Exhibit 13

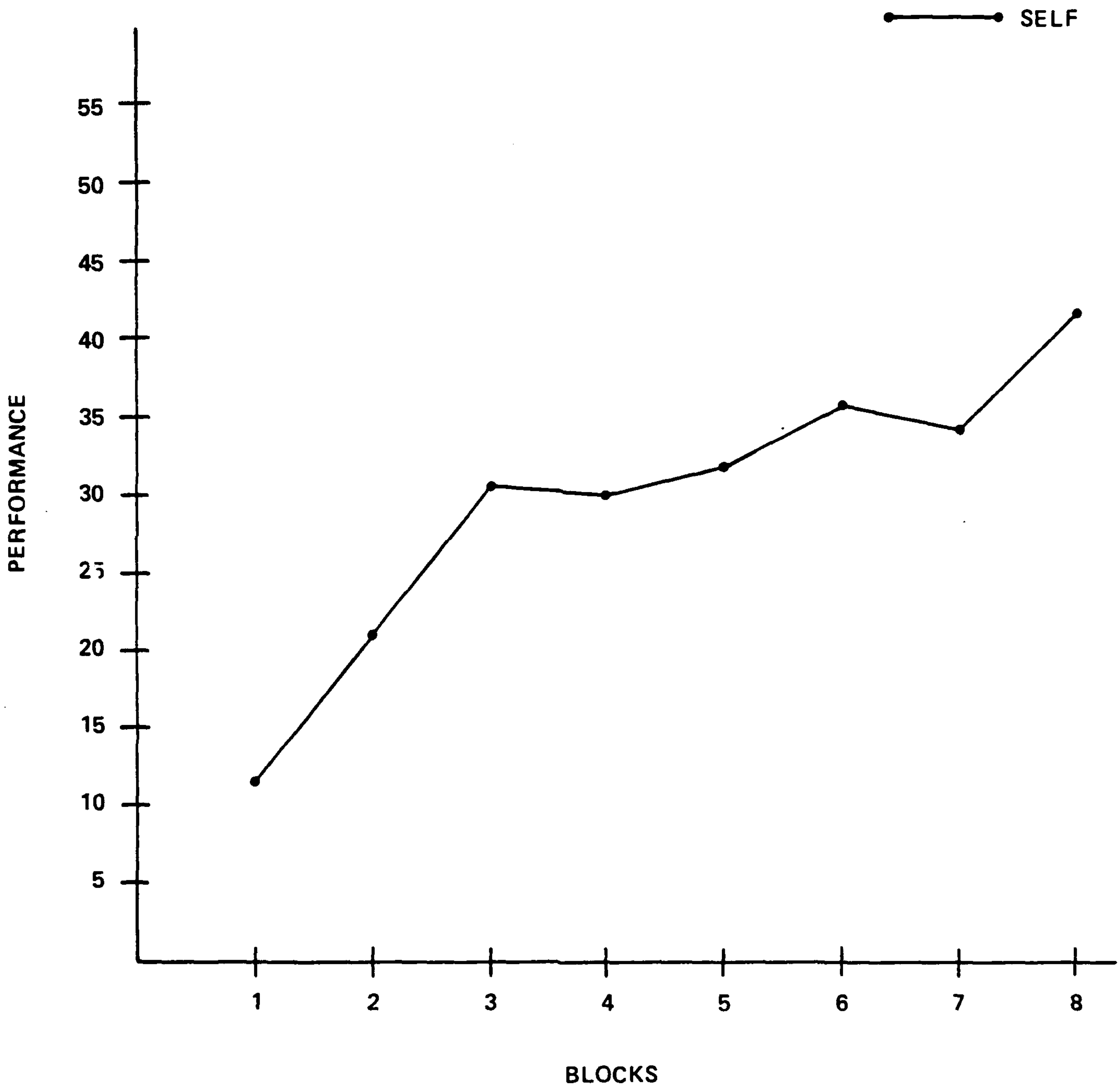
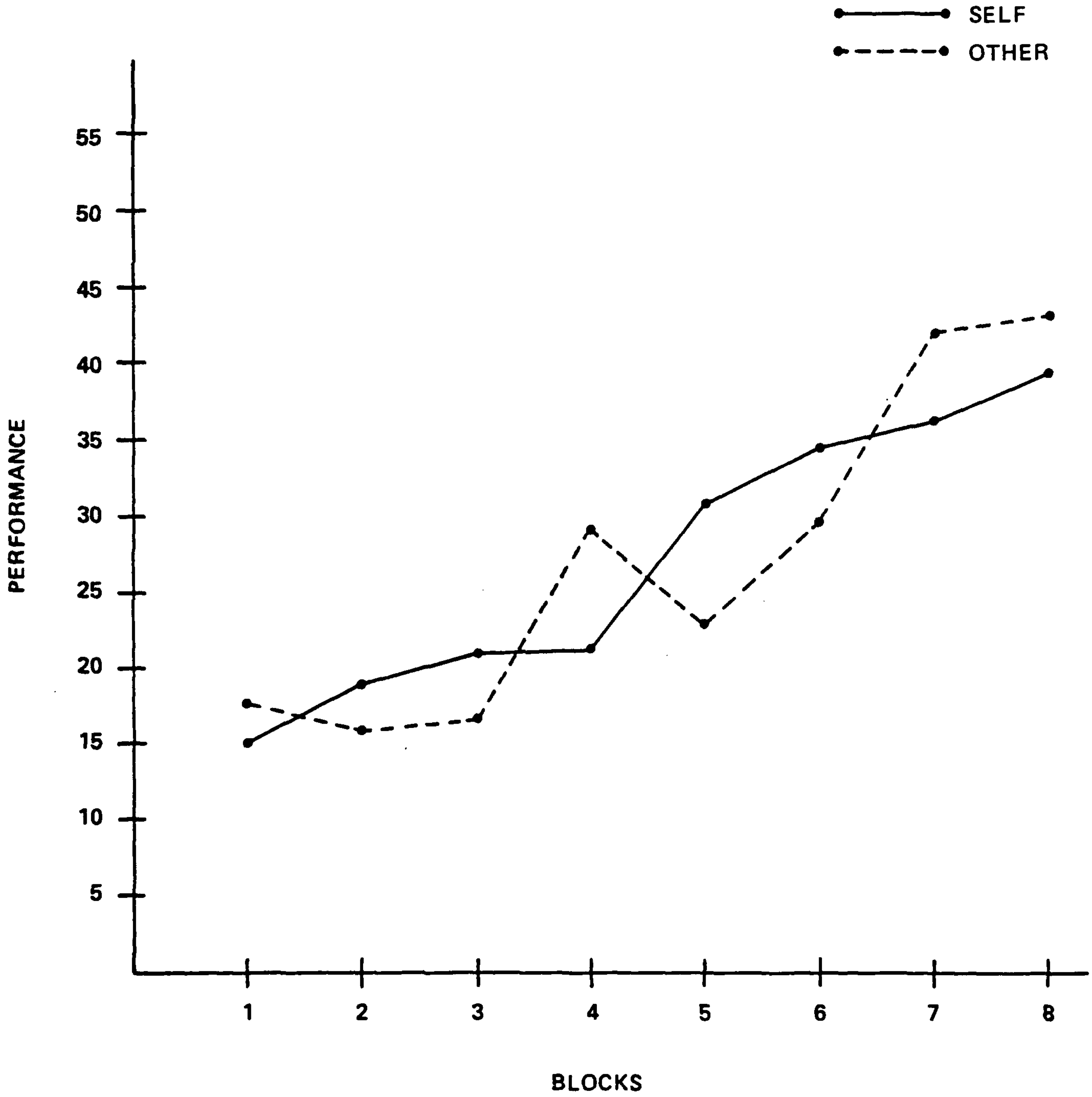

SELF
PERFORMANCE
55
50
45
40
35
30
25
20
15
10
5
1
2
3
4
5
6
7
8
BLOCKS

Exhibit 14


SELF
OTHER
PERFORMANCE
55
50
45
40
35
30
25
20
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10
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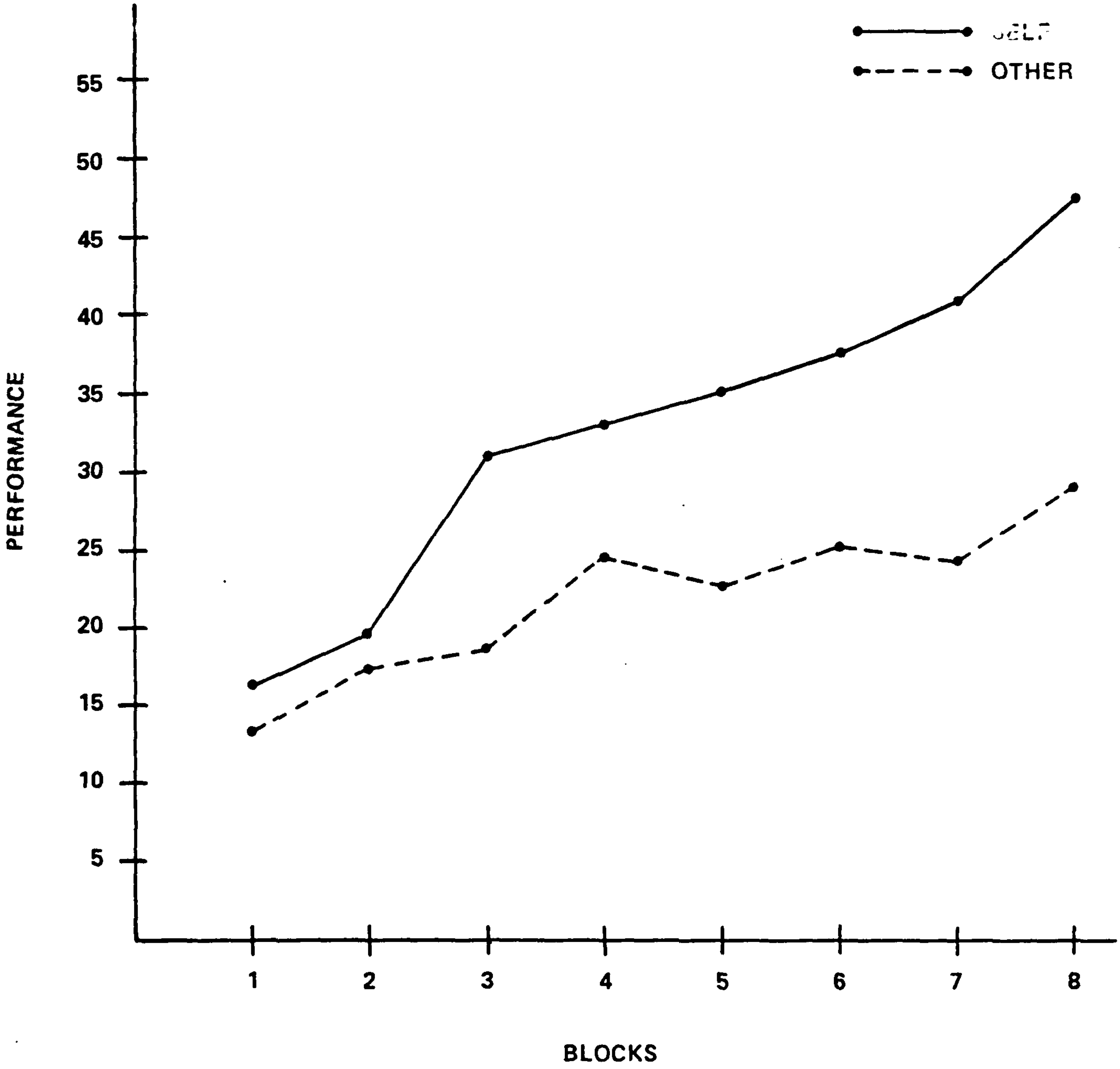
1
2
3
4
5
6
7
8
BLOCKS

Exhibit 15


OTHER
55
50
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35
30
25
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10
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PERFORMANCE
1
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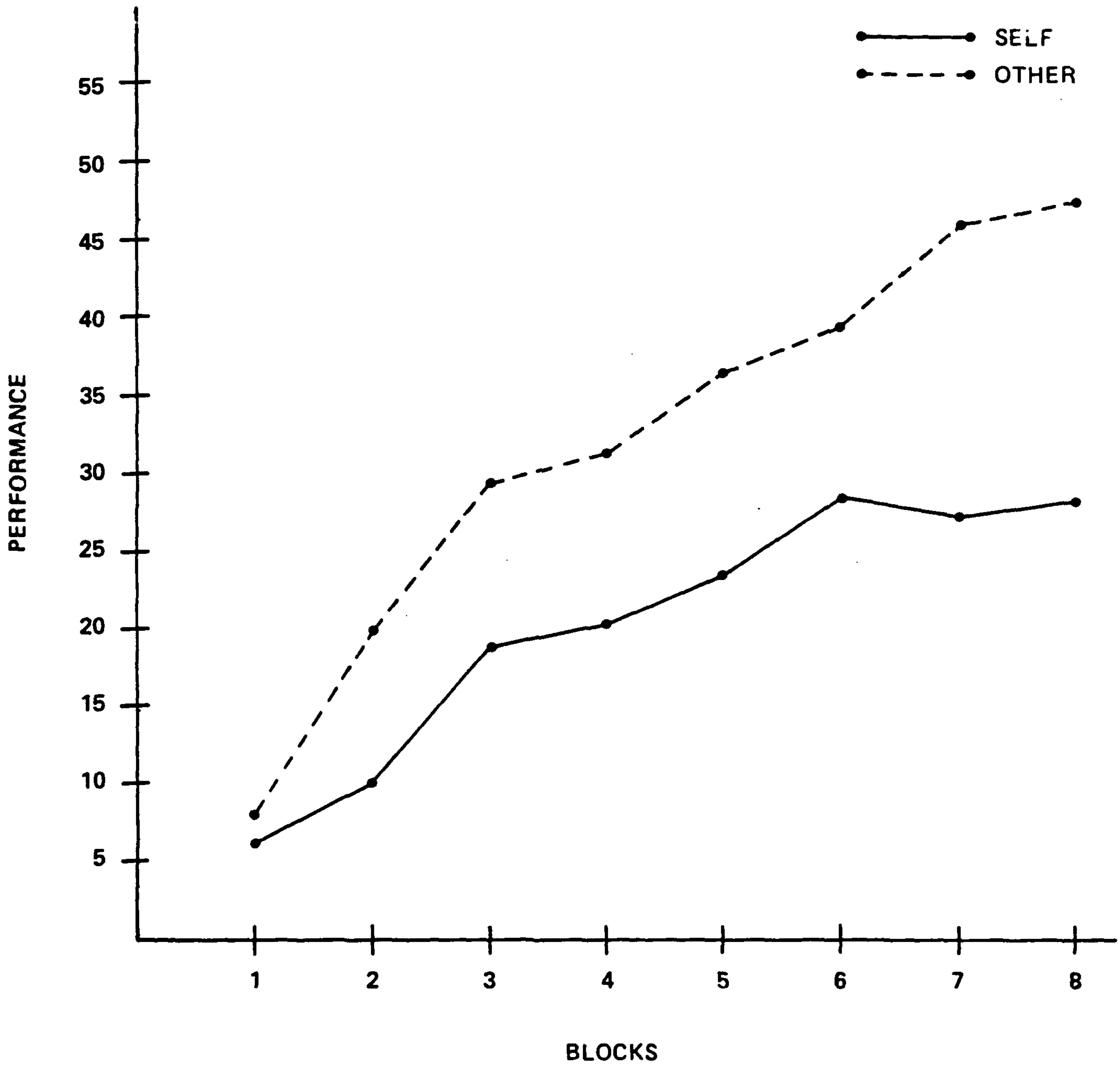
6
7
8
BLOCKS

Exhibit 16


SELF
OTHER
PERFORMANCE
55
50
45
40
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25
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15
10
5
1
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3
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5
6
7
8
BLOCKS

Exhibit 17

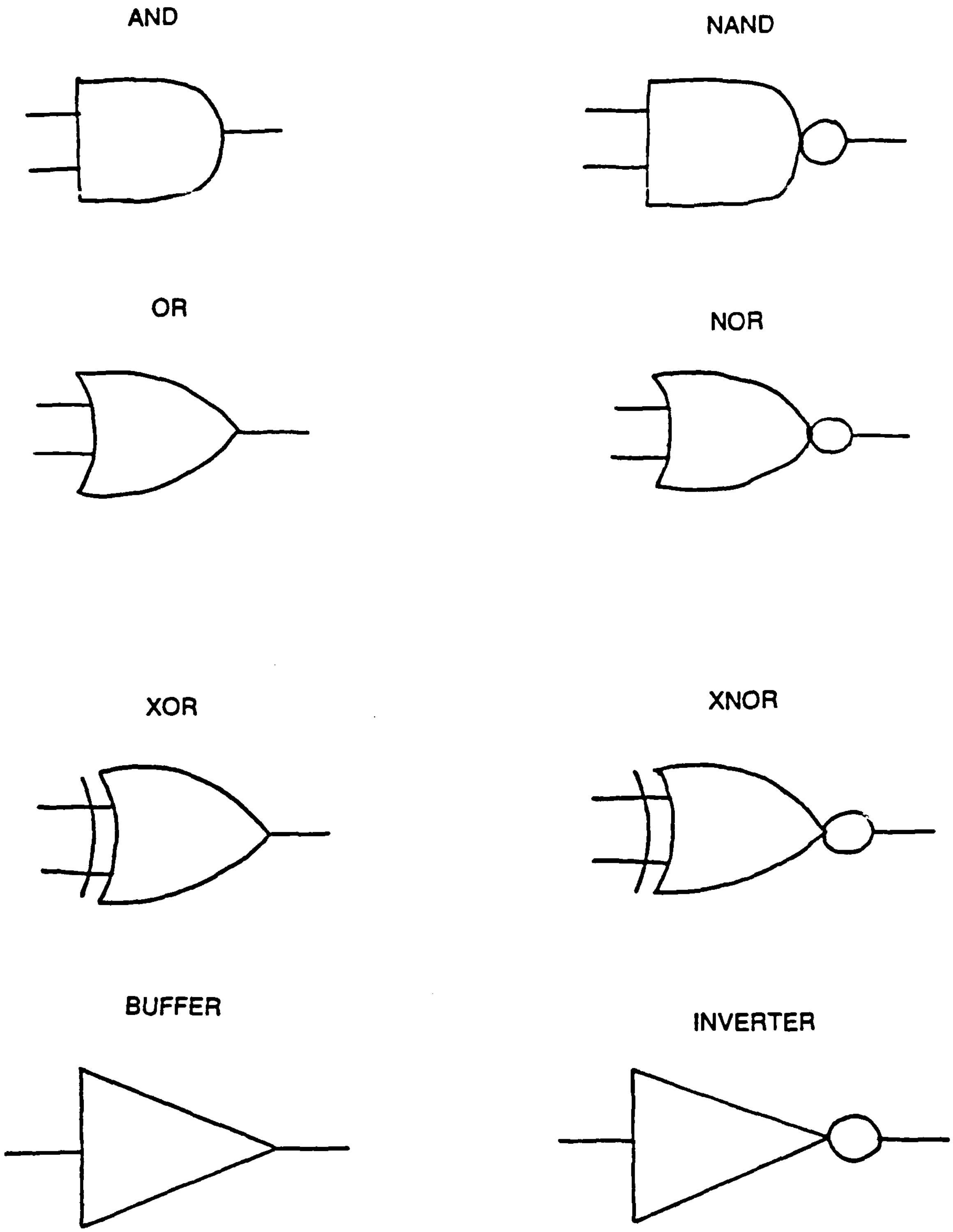
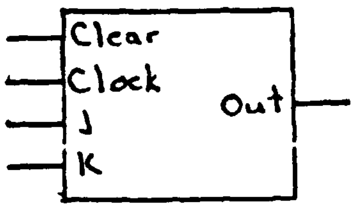
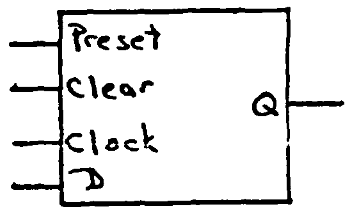


Exhibit 18

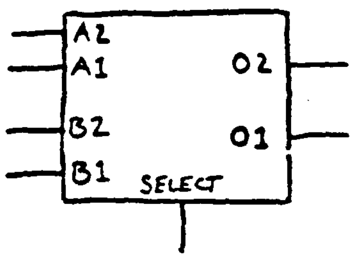
JK FLIP FLOP



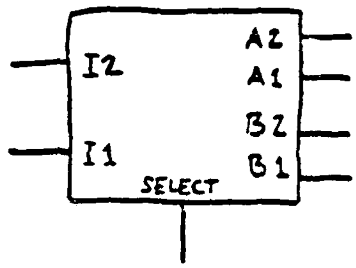
EDGE TRIGGER FLIP FLOP



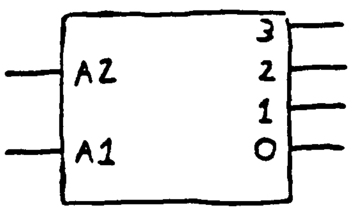
MULTIPLEXER



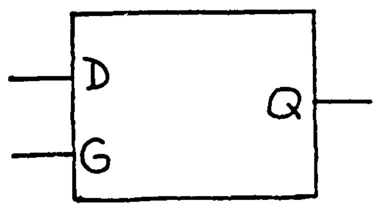
DeMULTIPLEXER



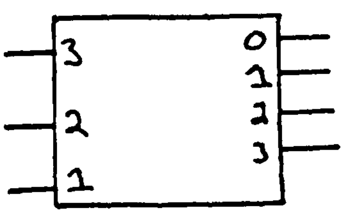
DECODER



LATCH



RUNS DETECTOR



COMPLEMENT

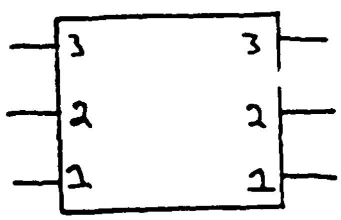
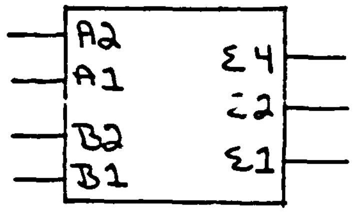
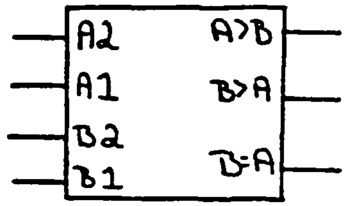


Exhibit 19

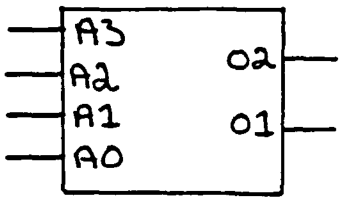
ADDER



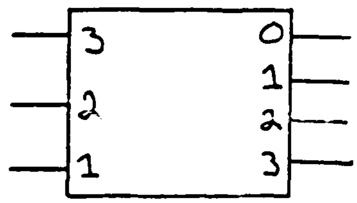
COMPARATOR



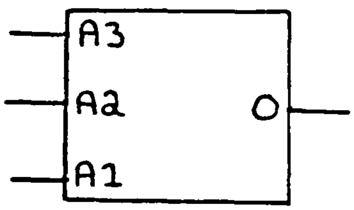
PRIORITY ENCODER



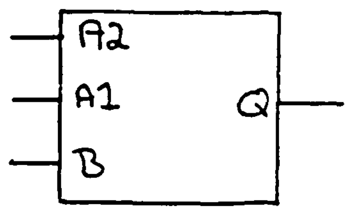
BIT COUNTER



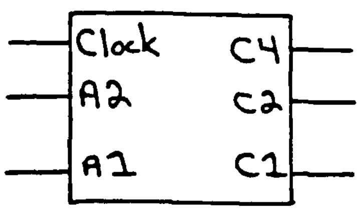
PARITY GENERATOR



MULTIVIBRATOR



COUNTER



SHIFT REGISTER

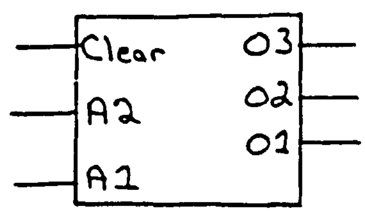


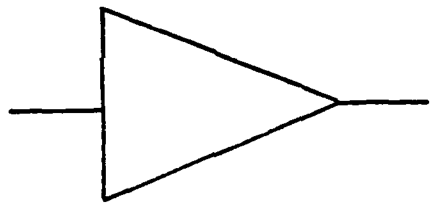
Exhibit 19 (cont.)

These are the components that you will work with today. Each component has its own rule for relating inputs to outputs. Please note that there are some constant rules that apply to all components:

0 stands for the inactive state.
1 stands for the active state.
X stands for either 1 or 0.
Some inputs are weighted more heavily than others. This means that *the displayed input value must be multiplied* by the weight to determine the actual input value.
For example, when input A2 equals 1, its value is 2.
When input A1 equals 1, its value is 1.

BUFFER

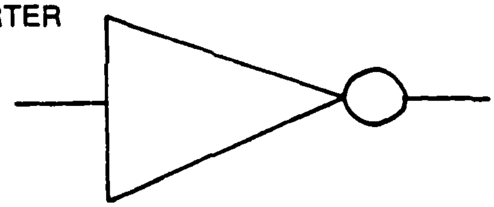
INPUTS	OUTPUT
1	1
0	0



Output is the same as the input.

INVERTER

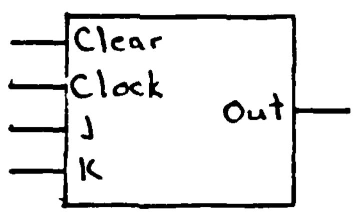
INPUTS	OUTPUT
1	0
0	1



Output is the opposite of the input.

JK FLIP FLOP

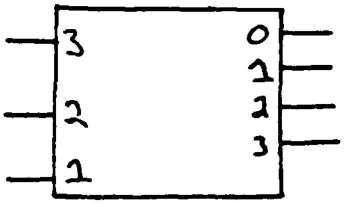
CLEAR	CLOCK	J	K	OUT
0	X	X	X	0
1	P	0	0	L
1	P	1	0	1
1	P	0	1	0
1	P	1	1	T
1	0	X	X	M



When the 'clear' input is 0; then the output is 0.
When the 'clear' input is 1, J and K are the relevant inputs.

RUNS DETECTOR

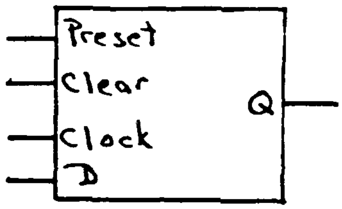
3	2	1	0	1	2	3
0	0	0	1	0	0	0
0	0	1	0	1	0	0
0	1	0	0	1	0	0
0	1	1	0	0	1	0
1	0	0	0	1	0	0
1	0	1	0	1	0	0
1	1	0	0	0	1	0
1	1	1	0	0	0	1



Count the number of 'active' (equal to 1) consecutive input states.
This number corresponds to where a 1 is placed in the output.
The rest of the outputs equal 0.

EDGE TRIGGER FLIP FLOP

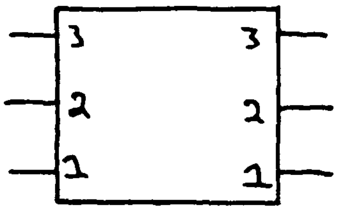
PRESET	CLEAR	CLOCK	D	Q
1	0	X	X	0
0	1	X	X	1
0	0	X	X	1
1	1	P	1	1
1	1	P	0	0
1	1	0	X	M



When pulse ('P') is present, the output equals the value of input D.
When there is no pulse ('P') and 'preset' and 'clear' are both 1, the output equals M.
When 'preset' equals 1 and 'clear' equals 0, the output equals 0.
When 'preset' equals 0, the output equals 1.

COMPLEMENT

3	2	1	3	2	1
0	0	0	1	1	1
0	0	1	1	1	0
0	1	0	1	0	1
0	1	1	1	0	0
1	0	0	0	1	1
1	0	1	0	1	0
1	1	0	0	0	1
1	1	1	0	0	0



The outputs are the opposite of the corresponding inputs.

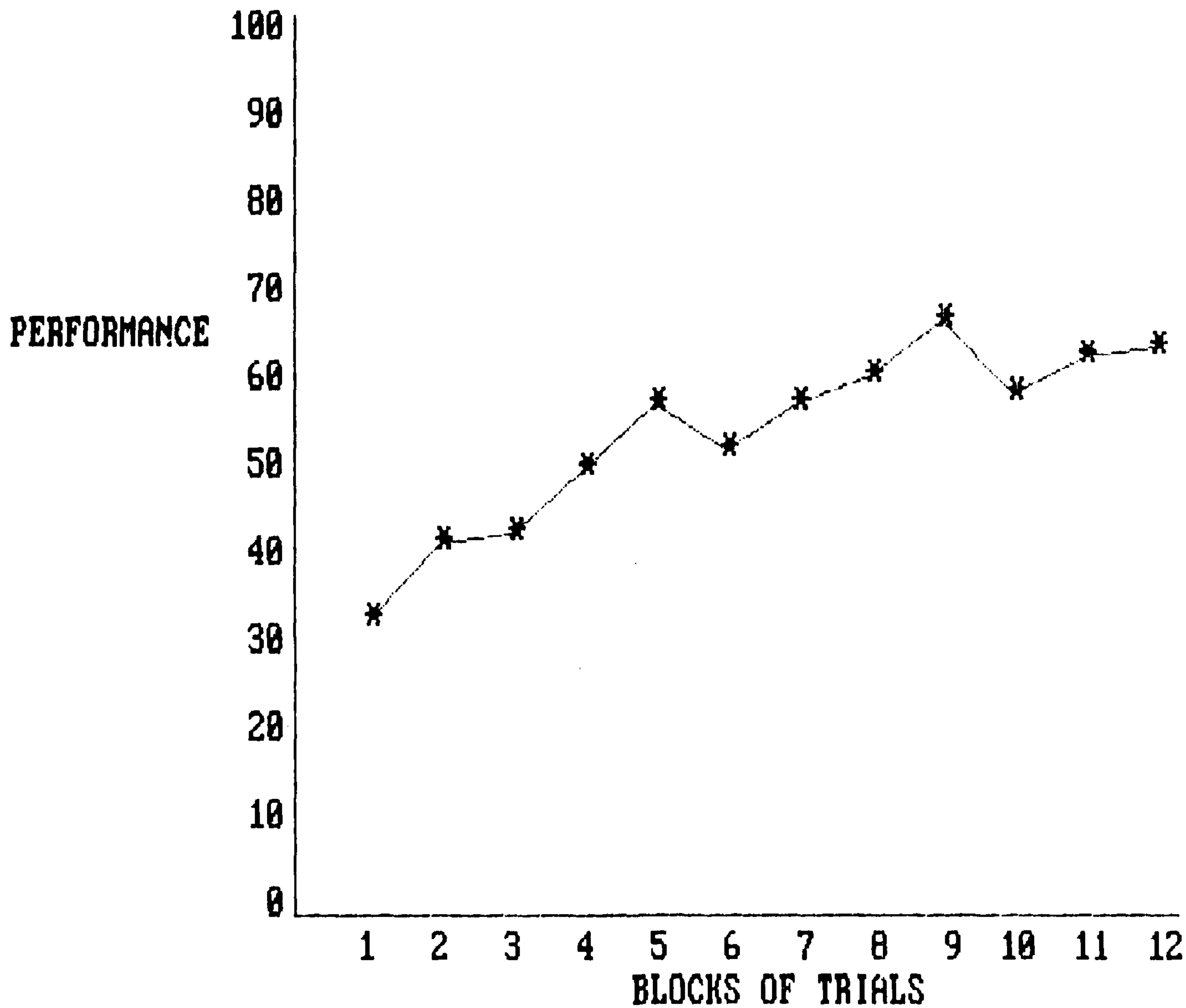

PERFORMANCE
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5
6
7
8
9
10
11
12
BLOCKS OF TRIALS

Exhibit 21

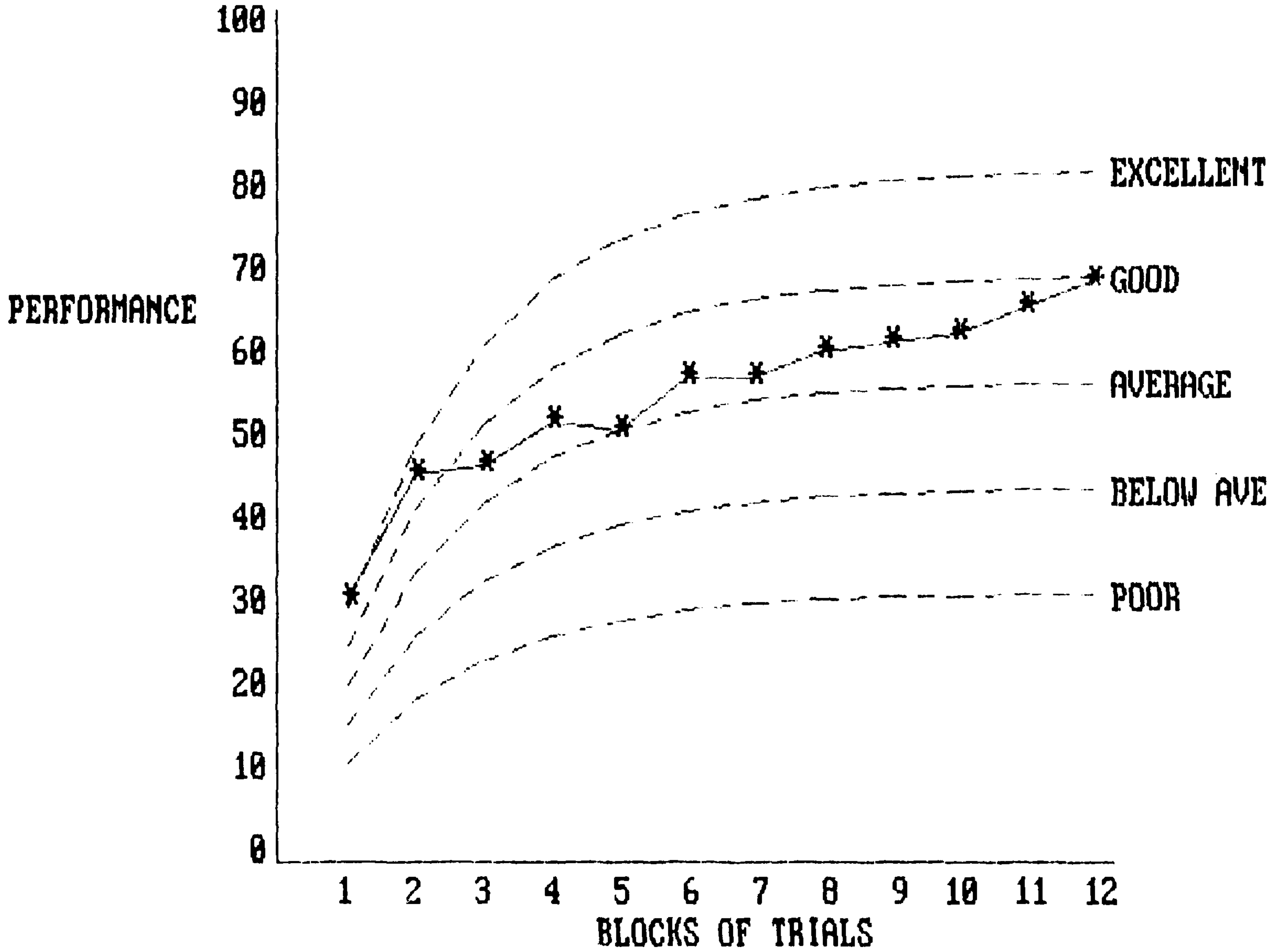
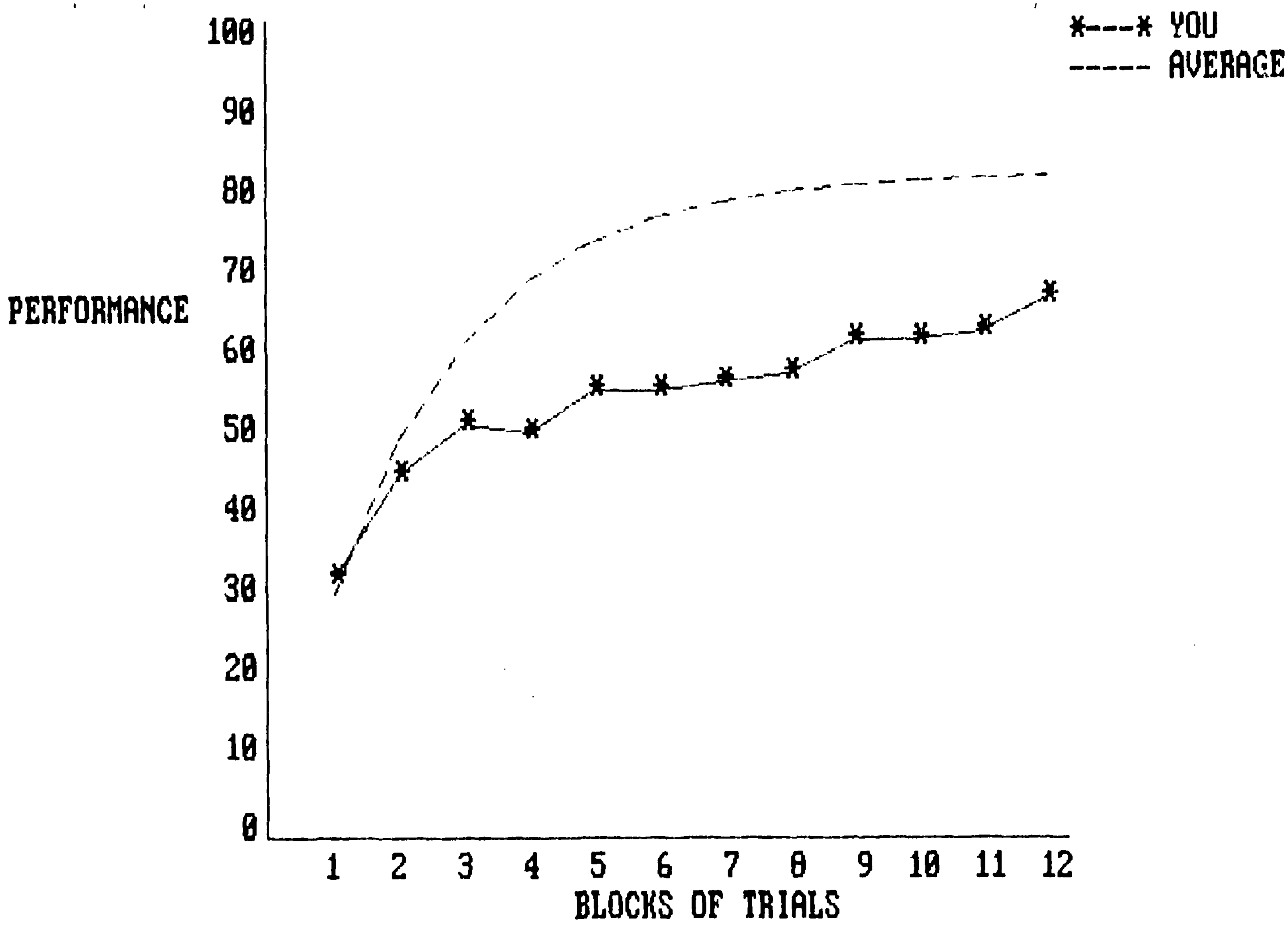

PERFORMANCE
100
90
80
70
60
50
40
30
20
10
0
EXCELLENT
GOOD
AVERAGE
BELOW AVE
POOR
1
2
3
4
5
6
7
8
9
10
11
12
BLOCKS OF TRIALS

Exhibit 22



--- YOU
----- AVERAGE
100
90
80
70
60
50
40
30
20
10
0
PERFORMANCE
1
2
3
4
5
6
7
8
9
10
11
12
BLOCKS OF TRIALS

Exhibit 23

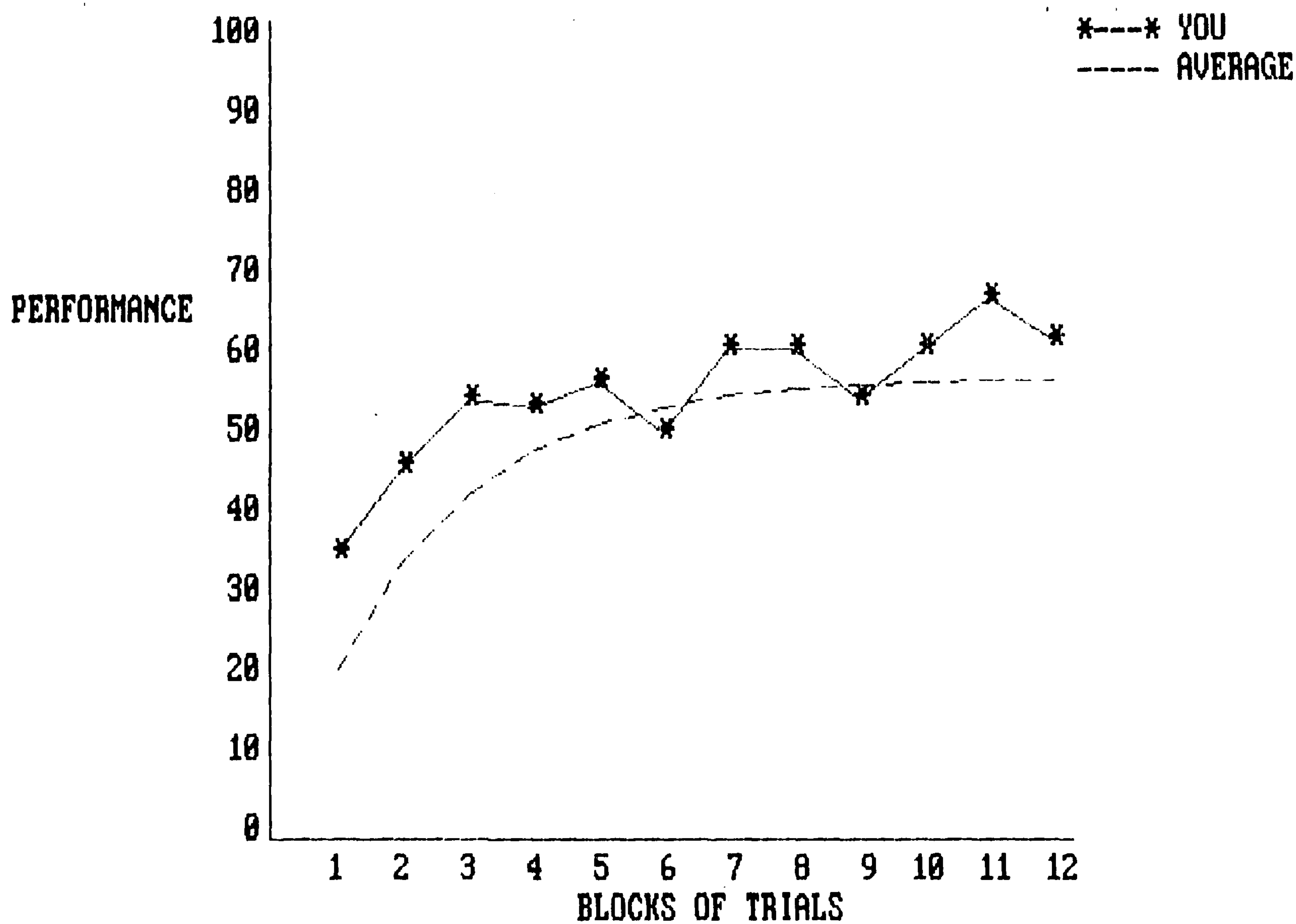

--- YOU
----- AVERAGE
PERFORMANCE
100
90
80
70
60
50
40
30
20
10
0
1
2
3
4
5
6
7
8
9
10
11
12
BLOCKS OF TRIALS

Exhibit 24

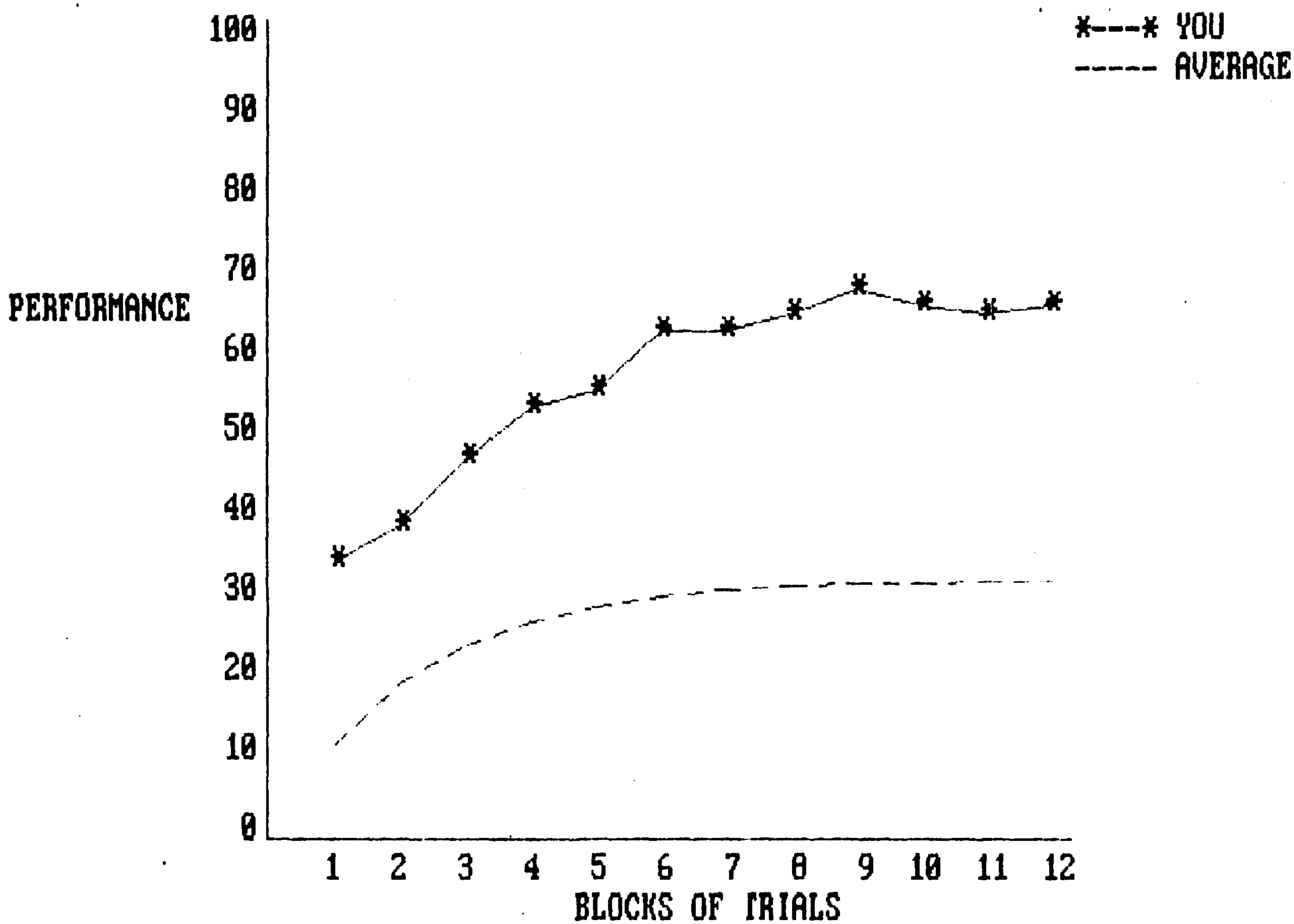

--- YOU
----- AVERAGE
PERFORMANCE
100
90
80
70
60
50
40
30
20
10
0
1 2 3 4 5 6 7 8 9 10 11 12
BLOCKS OF TRIALS

Exhibit 25

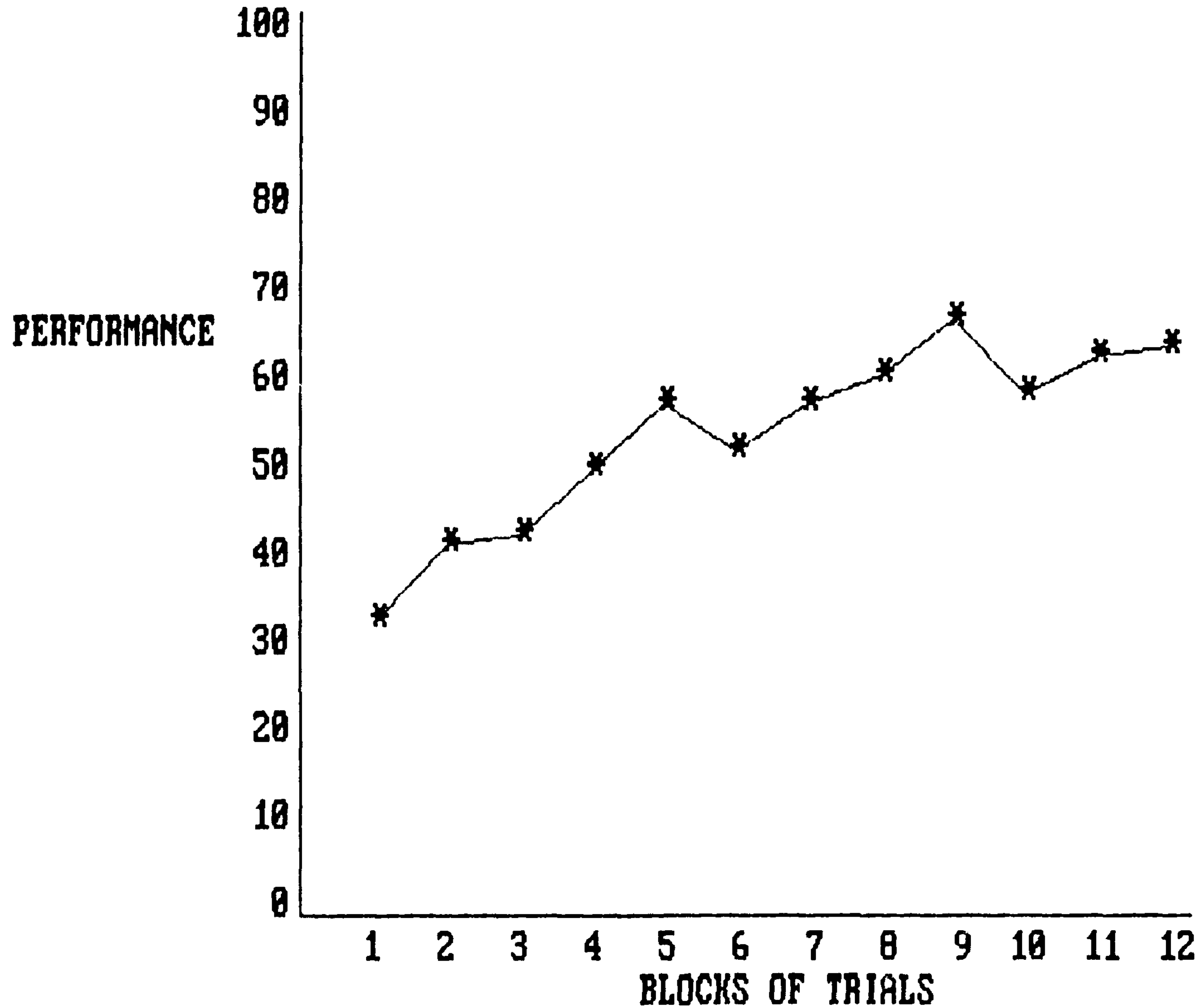

100
90
80
70
60
50
40
30
20
10
0
PERFORMANCE
1 2 3 4 5 6 7 8 9 10 11 12
BLOCKS OF TRIALS

Exhibit 26

"How do you think your performance compares with the performance of the average person on this task?"

Condition	M
Inferior Other	5.72
Average Other	4.41
Superior Other	3.59
Grade Band	4.81
Control	4.44

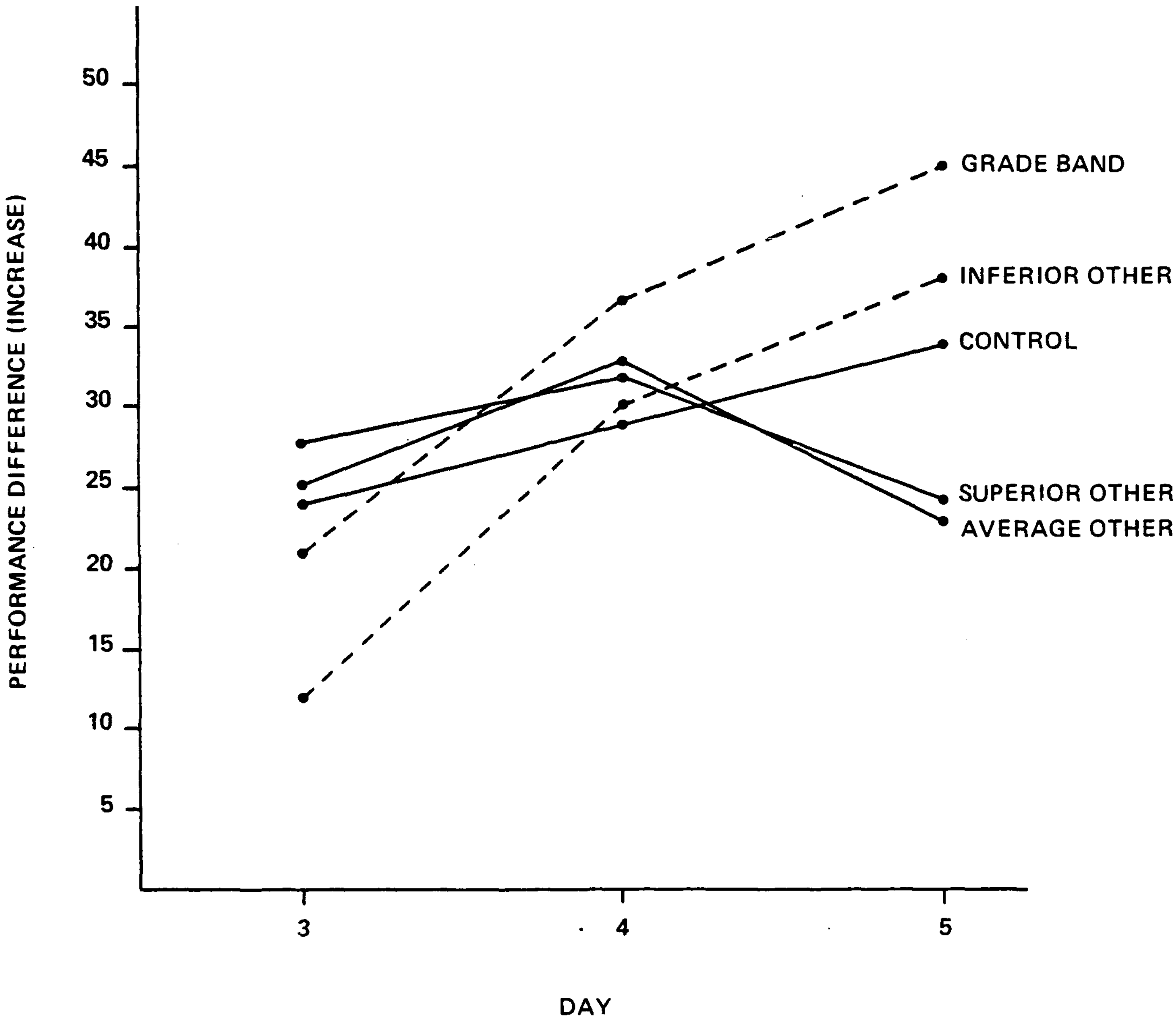
Exhibit 27

"How pleased are you with your overall performance on the task?"

<u>Condition</u>	<u>M</u>
Inferior Other	5.14
Average Other	4.62
Superior Other	3.49
Grade Band	5.00
Control	4.77

Attributions for Performance

Attribution	M
Effort	5.46
Ability	5.27
Luck	2.55
Task Difficulty	4.54



50
45
40
35
30
25
20
15
10
5
PERFORMANCE DIFFERENCE (INCREASE)
GRADE BAND
INFERIOR OTHER
CONTROL
SUPERIOR OTHER
AVERAGE OTHER
3
4
5
DAY

Exhibit 30

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